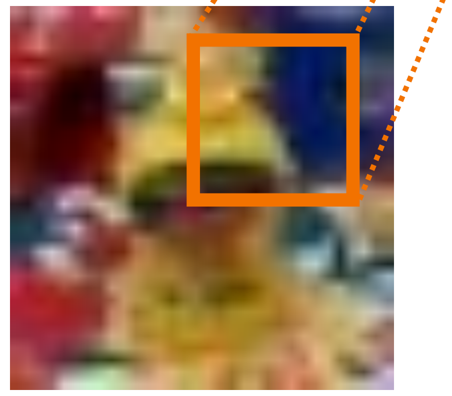
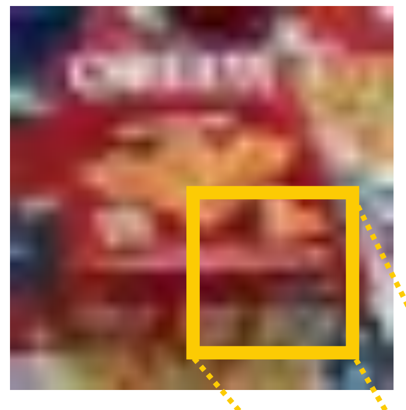
DeepRob



Lecture 8
CNN Architectures
University of Michigan and University of Minnesota



Office Hours Schedule

	Monday 01/30	Tuesday 01/31	Wednesday 02/01	Thursday 02/02	Friday 02/03
9:00 AM					
9:30 AM					
10:00 AM					
10:30 AM					
11:00 AM					
11:30 AM					
12:00 PM					
12:30 PM					
1:00 PM				**Jiyue's Office Hours** 1:00 PM–3:00 PM 2320 FMCRB Zoom Link	
1:30 PM			**Anthony's Office Hours** 1:30 PM–3:00 PM 3320 FMCRB Zoom Link		
2:00 PM		**Huijie's Office Hours** 2:00 PM–3:00 PM 2320 FMCRB Zoom Link			
	Huijie's Office Hours 2:30 PM–3:30 PM 2320 FMCRB Zoom Link				
		Lecture 8 3:00 PM–4:30 PM 1060 FMCRB Zoom Link		**Lecture 9** 3:00 PM–4:30 PM 1060 FMCRB Zoom Link	
3:30 PM					
4:00 PM					
4:30 PM		**Anthony's Office Hours** 4:30 PM–5:30 PM 1060 FMCRB		**Anthony's Office Hours** 4:30 PM–5:30 PM 1060 FMCRB	**Discussion 5** 4:30 PM–5:30 PM 1060 FMCRB Zoom Link
5:00 PM					
5:30 PM					**Anthony's Office Hours** 5:30 PM–6:30 PM 1060 FMCRB
6:00 PM					

Project 2—Updates

- Instructions available on the website
  - Here: deeprob.org/projects/project2/
- Starter code sent via email
- Implement two-layer neural network and generalize to FCN
- **Autograder will be available in next day or so**
- **Due Thursday, February 9th 11:59 PM EST**

Final Project Overview

- Research-oriented final project
  - Instead of a final exam!

- Objectives
  - Gain experience reading literature
  - Reproduce published results
  - Propose a new idea and test the results!

Final Project Overview

- Research-oriented final project
  - Instead of a final exam!

Can be completed in teams of 1-3 people

- Objectives
  - Gain experience reading literature
  - Reproduce published results
  - Propose a new idea and test the results!

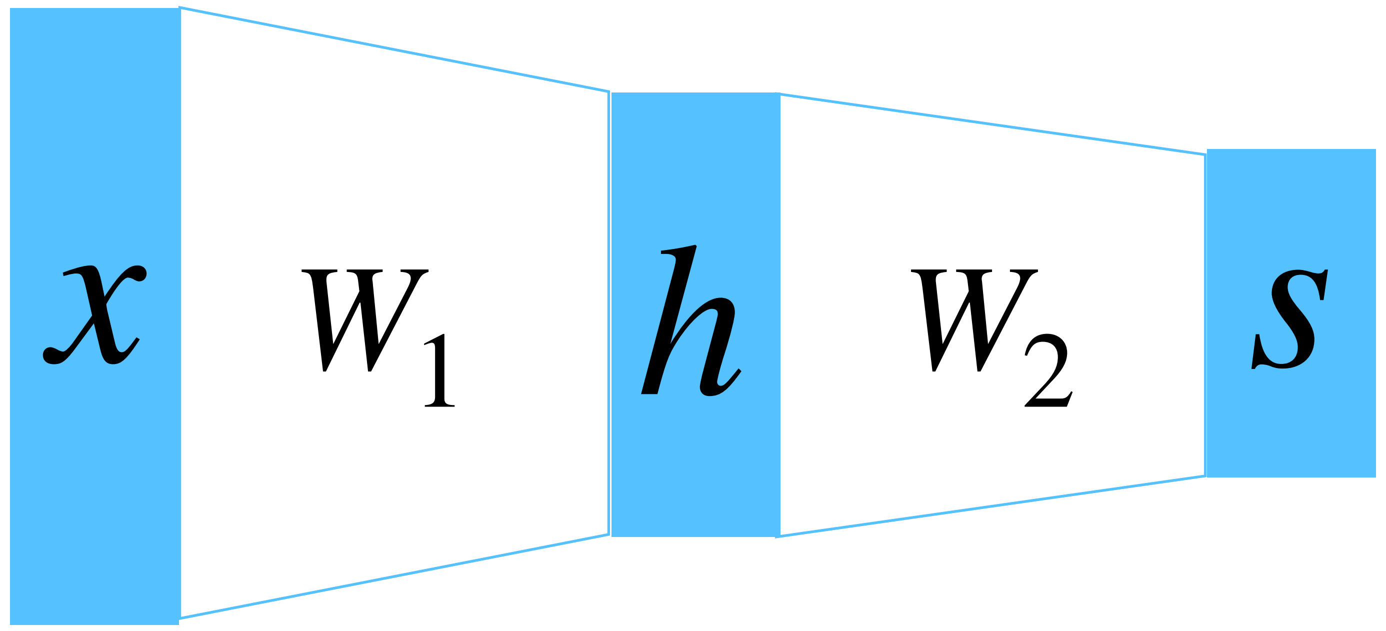
Final Project Paper Selection Survey

- Published on gradescope
- To gauge your areas of interest
- Used for forming teams

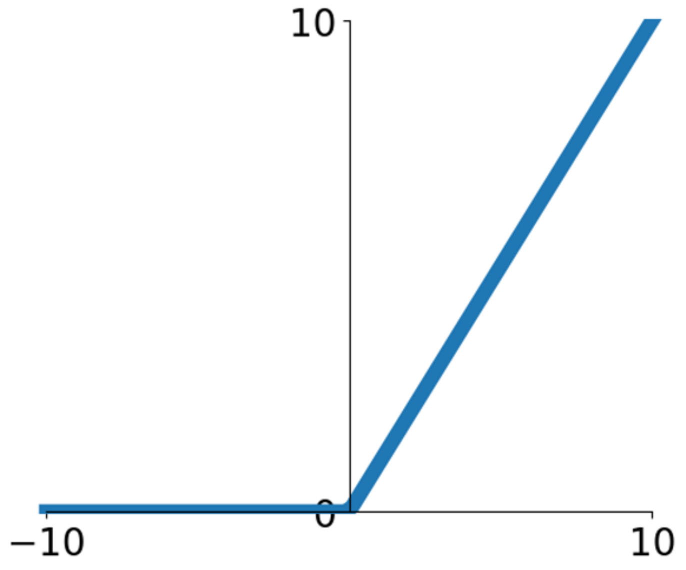
- **Due Friday, February 3rd 11:59 PM EST**

Recap: Components of Convolutional Network

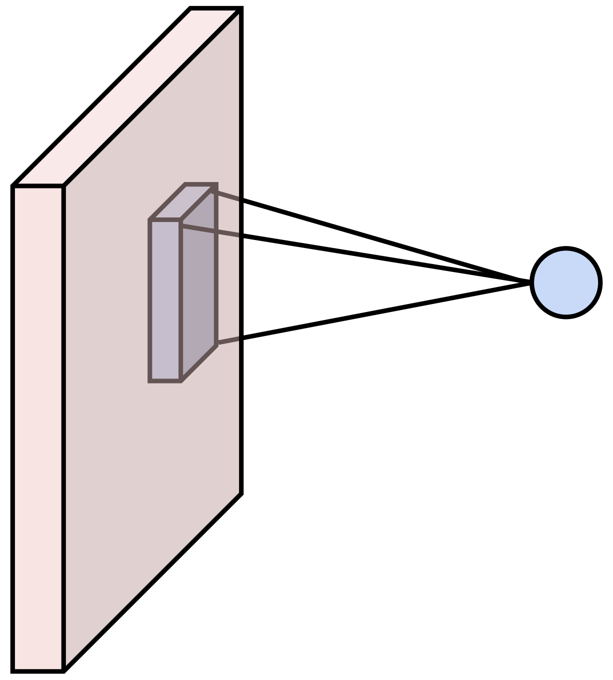
Fully-Connected Layers



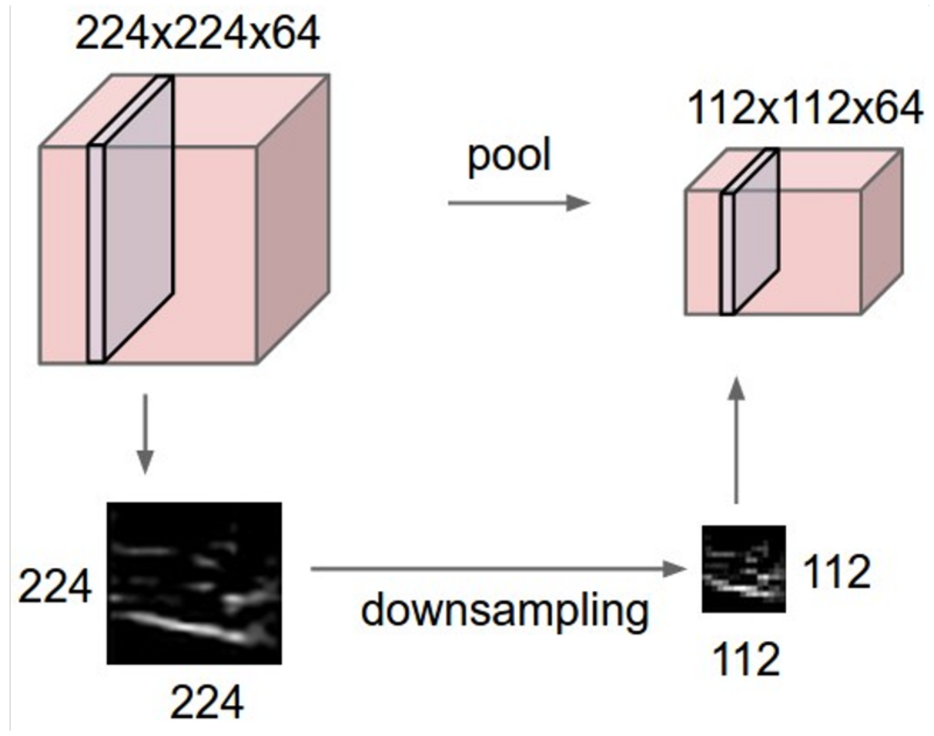
Activation Functions



Convolution Layers



Pooling Layers



Normalization

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Batch Normalization

Consider a single layer $y = Wx$

The following could lead to tough optimization:

- Inputs x are not *centered around zero* (need large bias)
- Inputs x have different scaling per-element
  (entries in W will need to vary a lot)

Idea: force inputs to be “nicely scaled” at each layer!

Batch Normalization

Idea: "Normalize" the inputs of a layer so they have zero mean and unit variance

We can normalize a batch of activations like this:

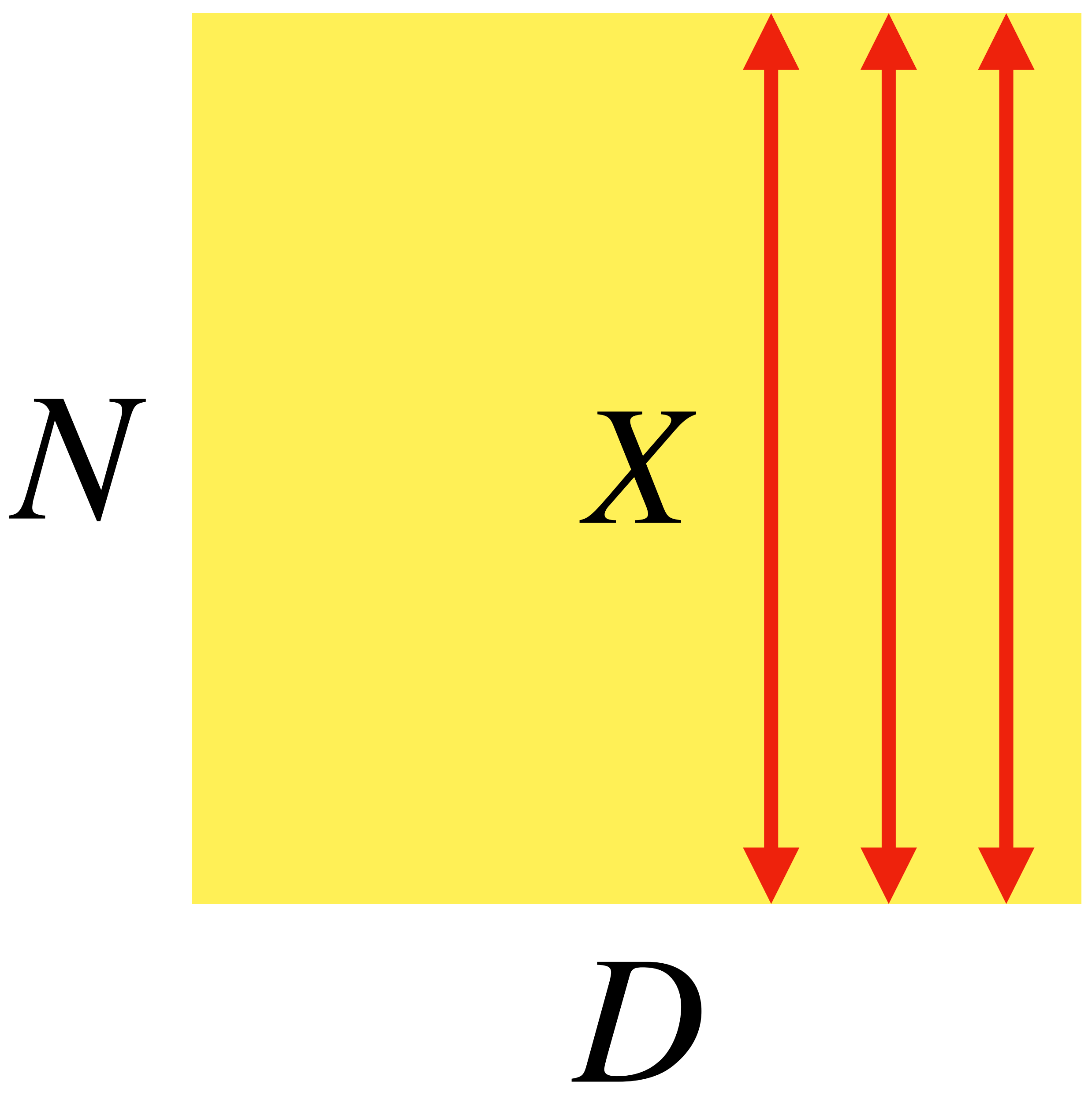
$$\hat{x} = \frac{x - E[x]}{\sqrt{Var[x]}}$$

This is a **differentiable function**, so we can use it as an operator in our networks and backprop through it!

Ioffe and Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," ICML 2015

Batch Normalization

Input: $x \in \mathbb{R}^{N \times D}$



$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} x_{i,j}$$

Per-channel mean, shape is D

$$\sigma_j^2 = \frac{1}{N}\sum_{i=1}^{N} (x_{i,j} - \mu_j)^2$$

Per-channel std, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

Normalized x, shape is $N \times D$

Problem: What if zero-mean, unit variance is too hard of a constraint?

Ioffe and Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," ICML 2015

Batch Normalization

Input: $x \in \mathbb{R}^{N \times D}$

Learnable scale and shift parameters: $\gamma, \beta \in \mathbb{R}^D$

Learning $\gamma = \sigma, \beta = \mu$ will recover the identity function (in expection)

$$\mu_j = \frac{1}{N} \sum_{i=1}^{N} x_{i,j}$$

Per-channel mean, shape is D

$$\sigma_j^2 = \frac{1}{N} \sum_{i=1}^{N} (x_{i,j} - \mu_j)^2$$

Per-channel std, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

Normalized x, shape is $N \times D$

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, shape is $N \times D$

Ioffe and Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," ICML 2015

Batch Normalization

Problem: Estimates depend on minibatch; can't do this at test-time

Input: $x \in \mathbb{R}^{N \times D}$

Learnable scale and shift parameters: $\gamma, \beta \in \mathbb{R}^D$

Learning $\gamma = \sigma, \beta = \mu$ will recover the identity function (in expection)

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$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, shape is $N \times D$

Batch Normalization: Test-Time

Input: $x \in \mathbb{R}^{N \times D}$

Learnable scale and shift parameters: $\gamma, \beta \in \mathbb{R}^{D}$

Learning $\gamma = \sigma, \beta = \mu$ will recover the identity function (in expection)

$\mu_j =$ (Running) average of values seen during training

Per-channel mean, shape is D

$\sigma_j^2 =$ (Running) average of values seen during training

Per-channel std, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

Normalized x, shape is $N \times D$

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, shape is $N \times D$

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Batch Normalization: Test-Time

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Learnable scale and shift parameters: $\gamma, \beta \in \mathbb{R}^D$

Learning $\gamma = \sigma, \beta = \mu$ will recover the identity function (in expection)

$\mu_j =$ (Running) average of values seen during training

Per-channel mean, shape is D

$$\mu_j^{test} = 0$$

For each training iteration:

$$\mu_j = \frac{i = 1}{N} x_{i,j}$$

$$\mu_j^{test} = 0.99 \mu_j^{test} + 0.01 \mu_j$$

(Similar for σ)

Ioffe and Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," ICML 2015

Batch Normalization: Test-Time

Input: $x \in \mathbb{R}^{N \times D}$

Learnable scale and shift parameters: $\gamma, \beta \in \mathbb{R}^{D}$

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Per-channel std, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

Normalized x, shape is $N \times D$

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, shape is $N \times D$

Ioffe and Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” ICML 2015

Batch Normalization: Test-Time

Input: $x \in \mathbb{R}^{N \times D}$

Learnable scale and shift parameters: $\gamma, \beta \in \mathbb{R}^D$

During testing batchnorm becomes a linear operator!
Can be fused with the previous fully-connected or conv layer

$\mu_j =$ (Running) average of values seen during training — Per-channel mean, shape is D

$\sigma_j^2 =$ (Running) average of values seen during training — Per-channel std, shape is D

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

Normalized x, shape is $N \times D$

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j$$

Output, shape is $N \times D$

Ioffe and Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," ICML 2015

Batch Normalization for Convents

Batch Normalization for **fully-connected** networks

$$x : N \times D$$

Normalize

$$\mu, \sigma : 1 \times D$$

$$\gamma, \beta : 1 \times D$$

$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Batch Normalization for **convolutional** networks (Spatial Batchnorm, BatchNorm2D)

$$x : N \times C \times H \times W$$

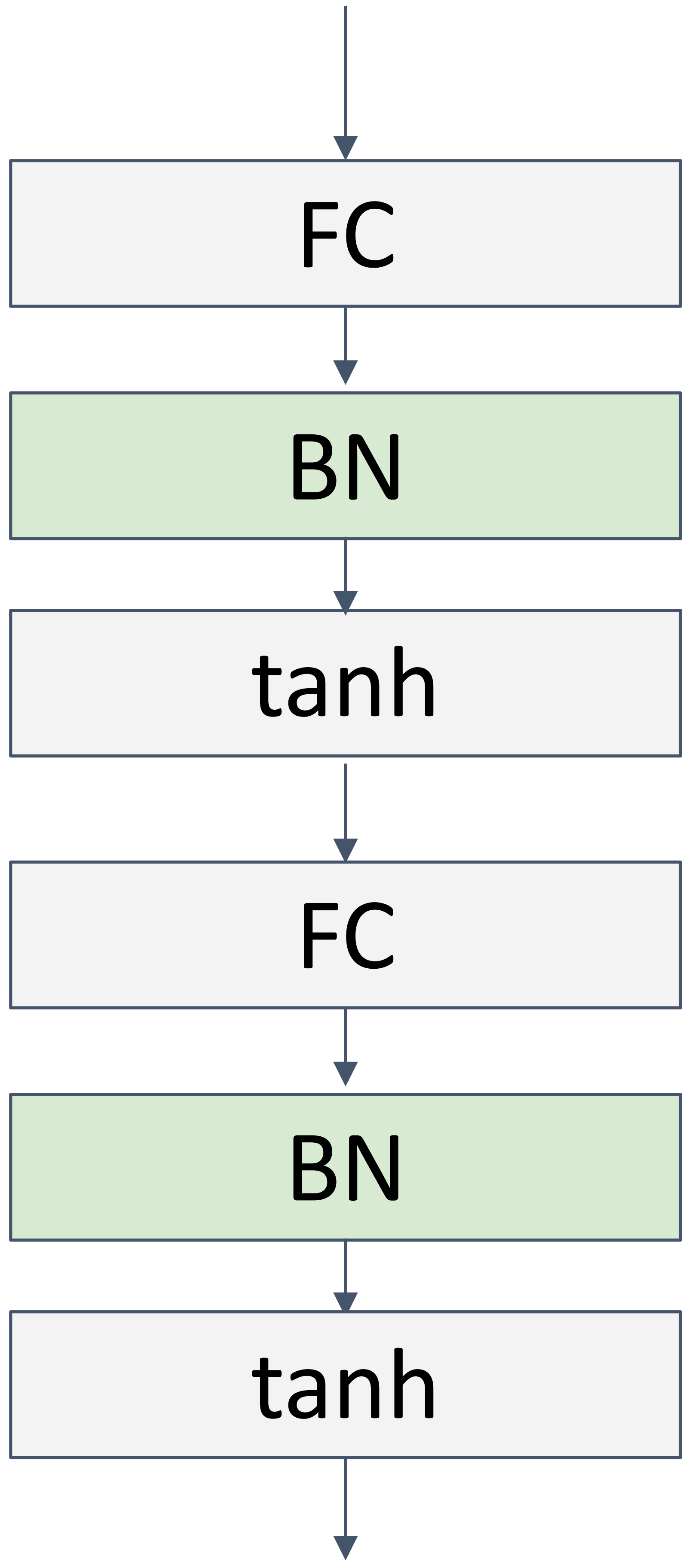
Normalize

$$\mu, \sigma : 1 \times C \times 1 \times 1$$

$$\gamma, \beta : 1 \times C \times 1 \times 1$$

$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Batch Normalization

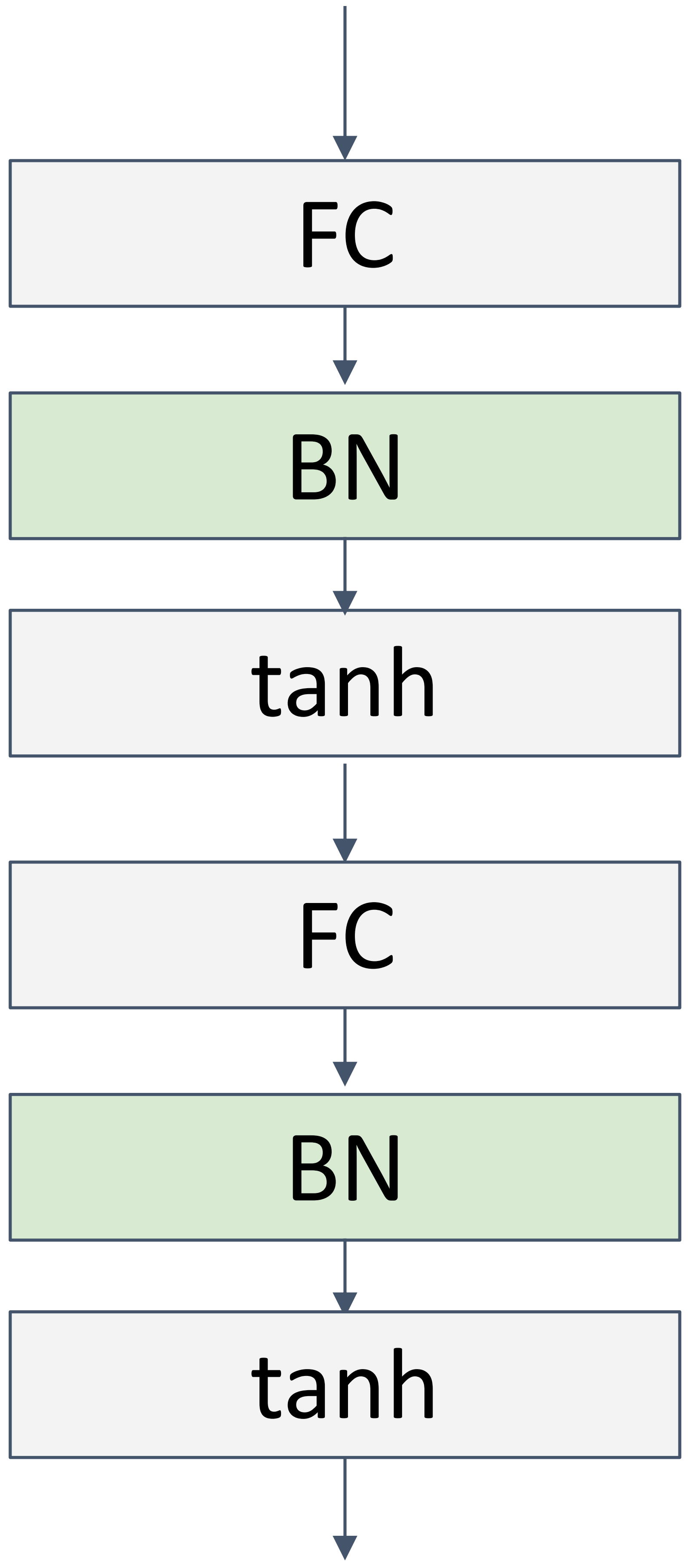


Usually inserted after Fully Connected or Convolutional layers, and before nonlinearity.

$$\hat{x} = \frac{x - E[x]}{\sqrt{Var[x]}}$$

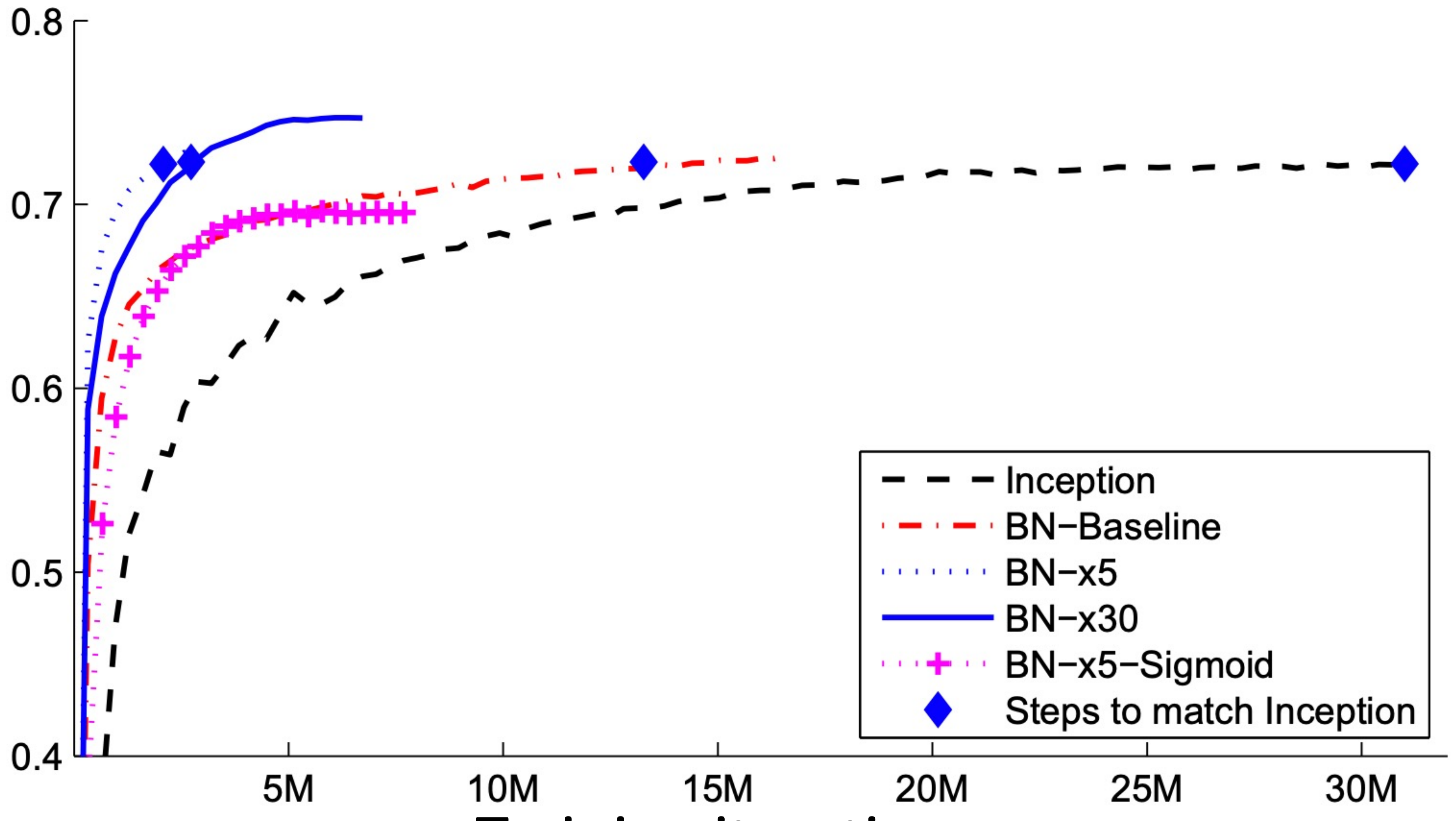
Ioffe and Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," ICML 2015

Batch Normalization



- Makes deep networks **much** easier to train!
- Allows higher learning rates, faster convergence
- Networks become more robust to initialization
- Acts as regularization during training.
- Zero overhead at test-time: can be fused with conv!

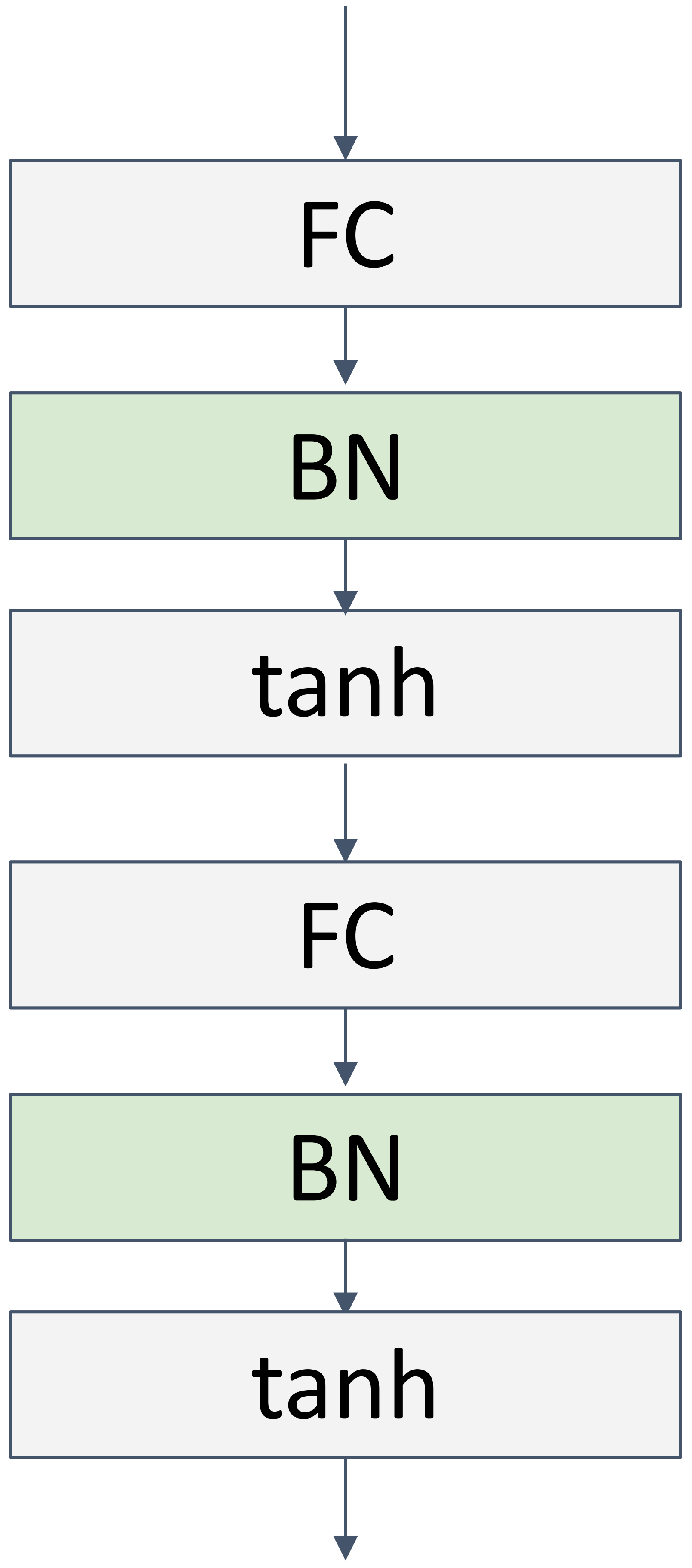
ImageNet accuracy



Training iterations

Ioffe and Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” ICML 2015

Batch Normalization



- Makes deep networks **much** easier to train!
- Allows higher learning rates, faster convergence
- Networks become more robust to initialization
- Acts as regularization during training.
- Zero overhead at test-time: can be fused with conv!
- Not well-understood theoretically (yet)
- Behaves differently during training and testing: this is very common source of bugs!

Ioffe and Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," ICML 2015

Layer Normalization

Batch Normalization for **fully-connected** networks

$$x : N \times D$$

Normalize
$$\mu, \sigma : 1 \times D$$

$$\gamma, \beta : 1 \times D$$

$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Layer Normalization for **fully-connected** networks
Same behavior at train and test!
Used in RNNs, Transformers

$$x : N \times D$$

Normalize
$$\mu, \sigma : N \times 1$$

$$\gamma, \beta : 1 \times D$$

$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Instance Normalization

Batch Normalization for **convolutional** networks

$$x : N \times C \times H \times W$$

Normalize

$$\mu, \sigma : 1 \times C \times 1 \times 1$$

$$\gamma, \beta : 1 \times C \times 1 \times 1$$

$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Instance Normalization for **convolutional** networks

$$x : N \times C \times H \times W$$

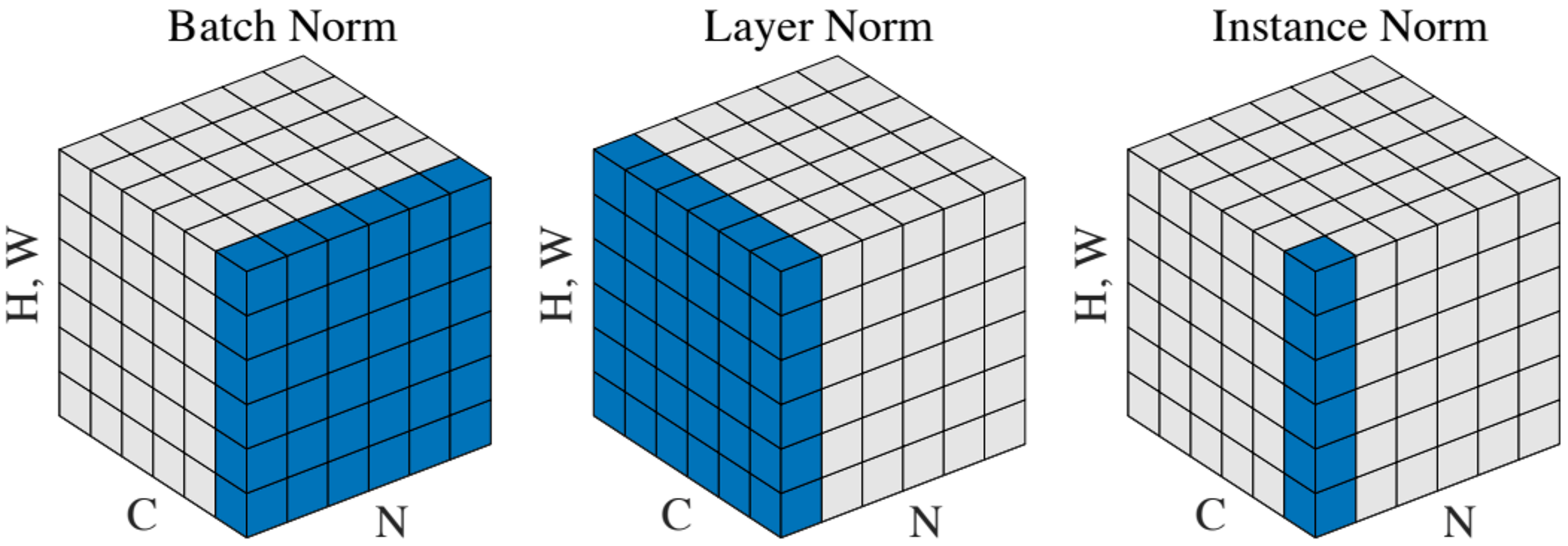
Normalize

$$\mu, \sigma : N \times C \times 1 \times 1$$

$$\gamma, \beta : 1 \times C \times 1 \times 1$$

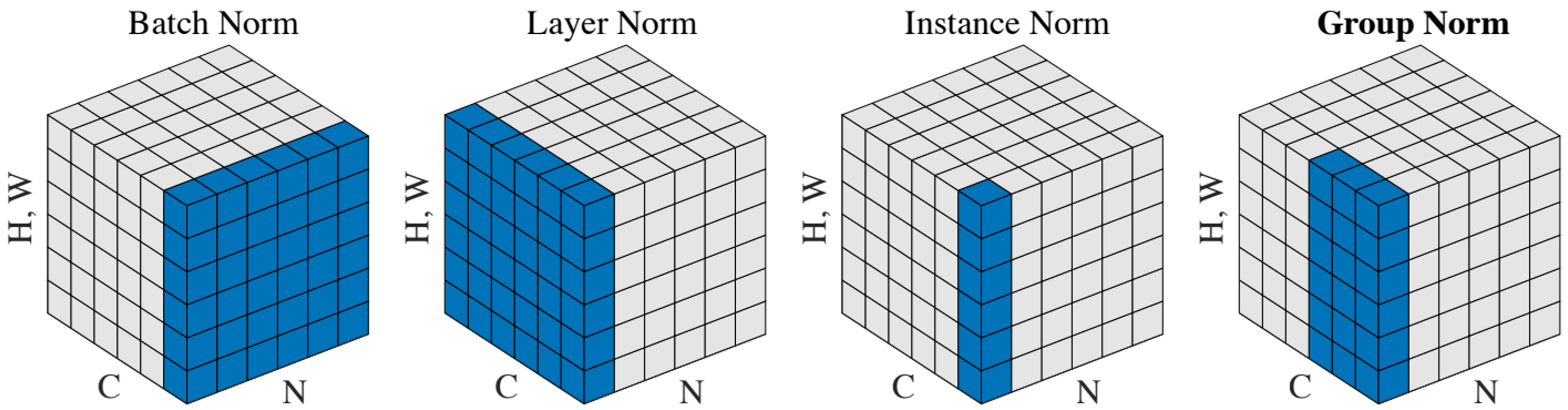
$$y = \frac{(x - \mu)}{\sigma}\gamma + \beta$$

Comparison of Normalization Layers



Wu and He, “Group Normalization,” ECCV 2018

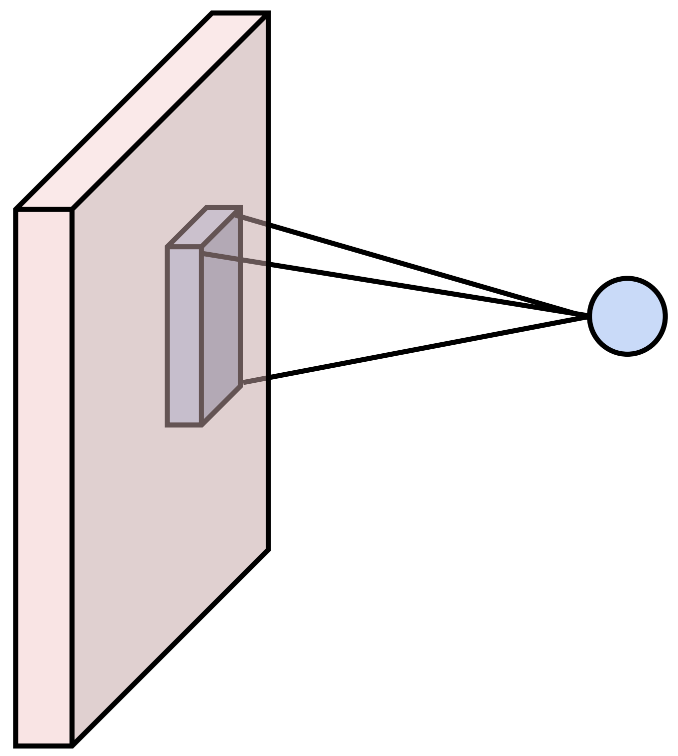
Group Normalization



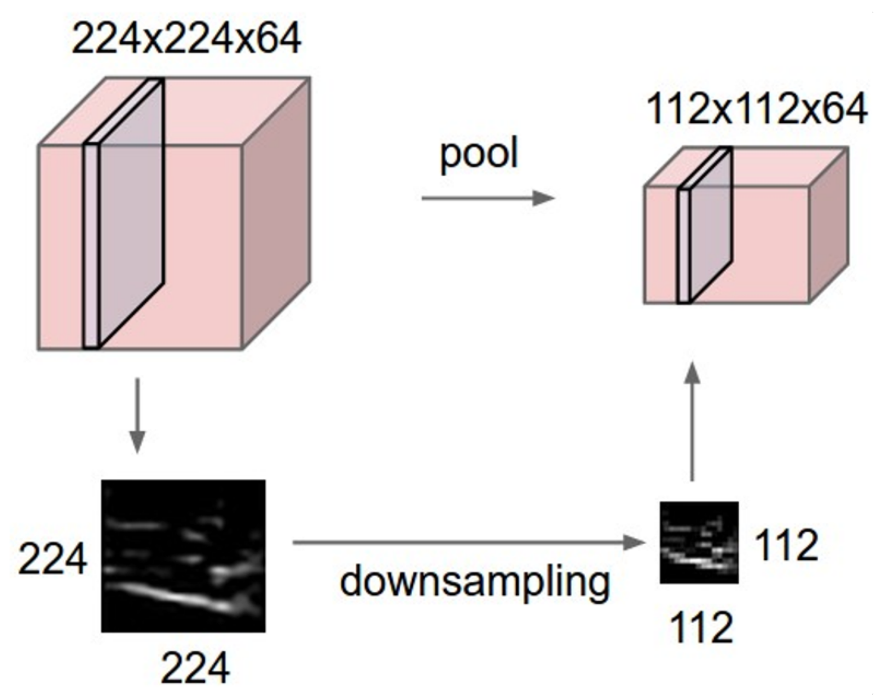
Wu and He, "Group Normalization," ECCV 2018

Components of Convolutional Networks

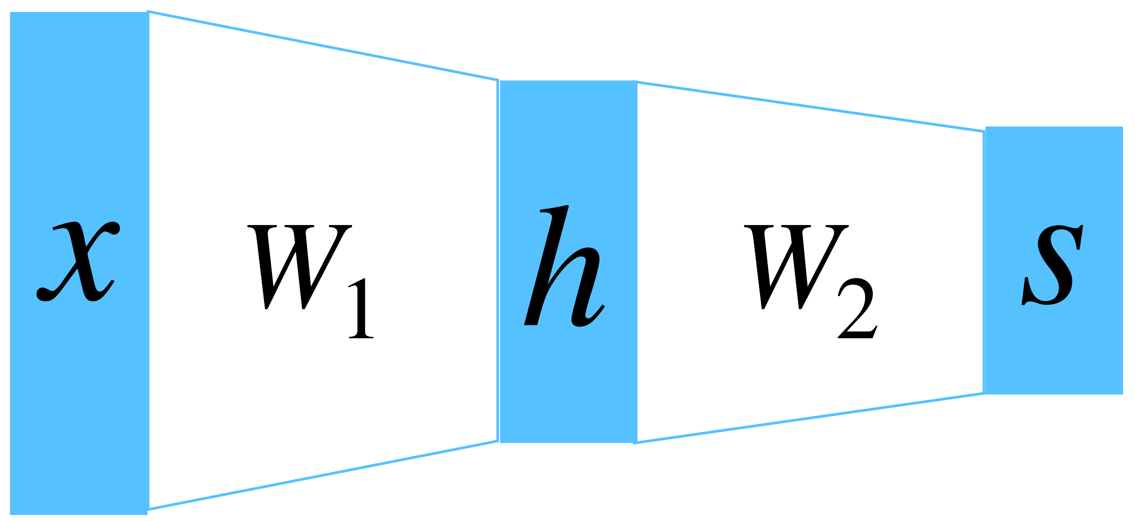
Convolution Layers



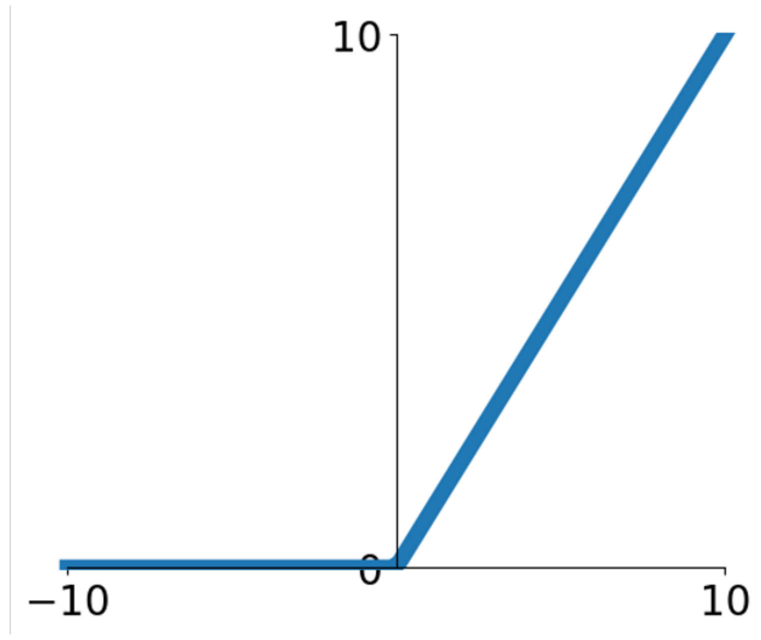
Pooling Layers



Fully-Connected Layers



Activation Function

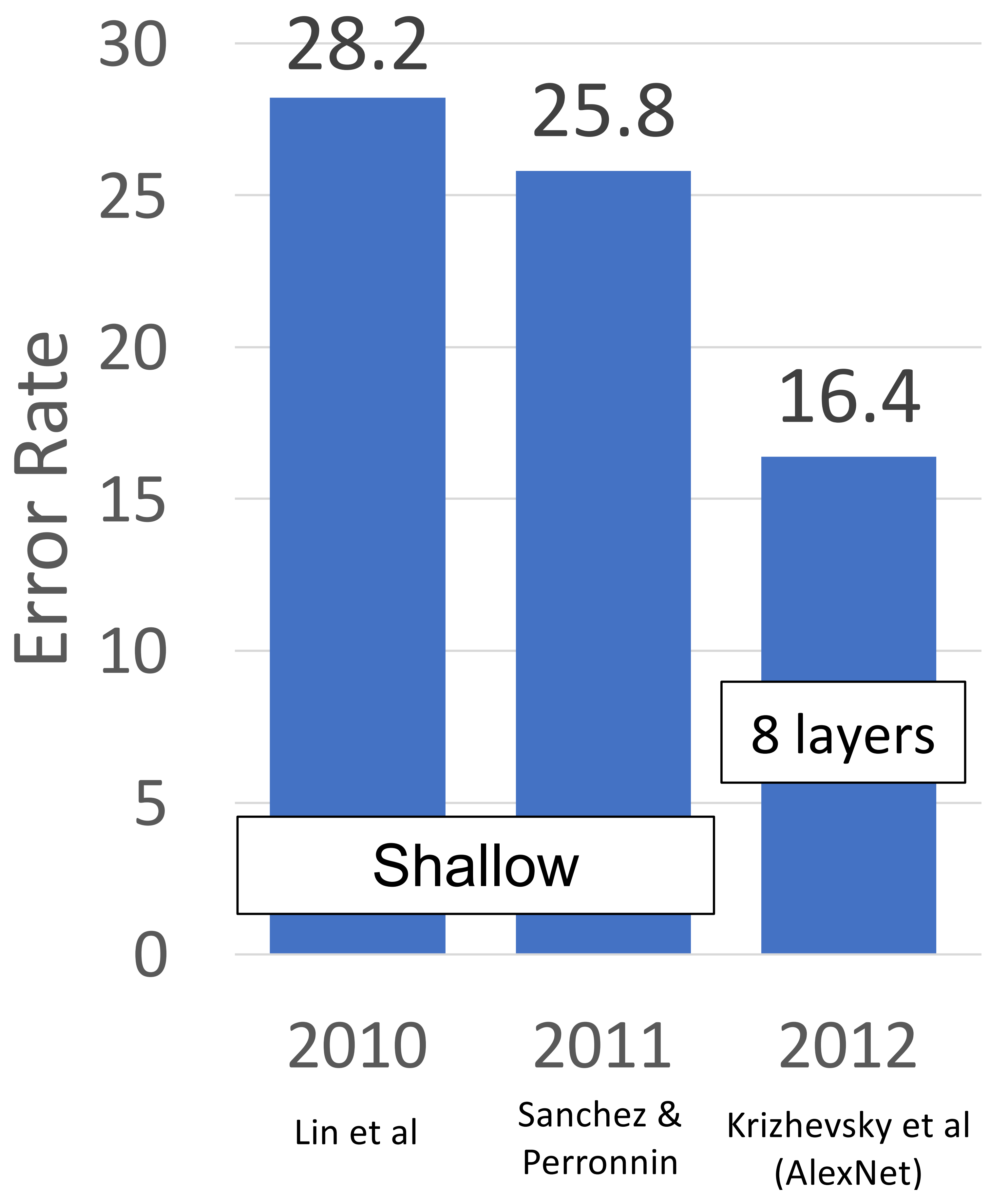


Normalization

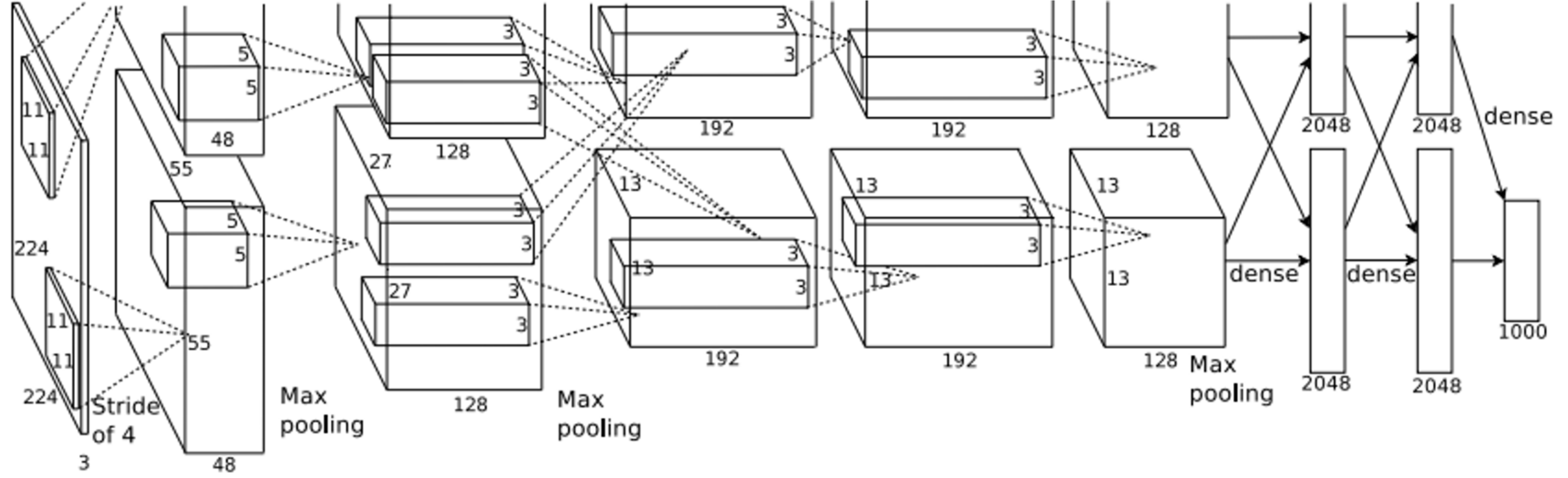
$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

Question: How should we put them together?

ImageNet Classification Challenge



AlexNet



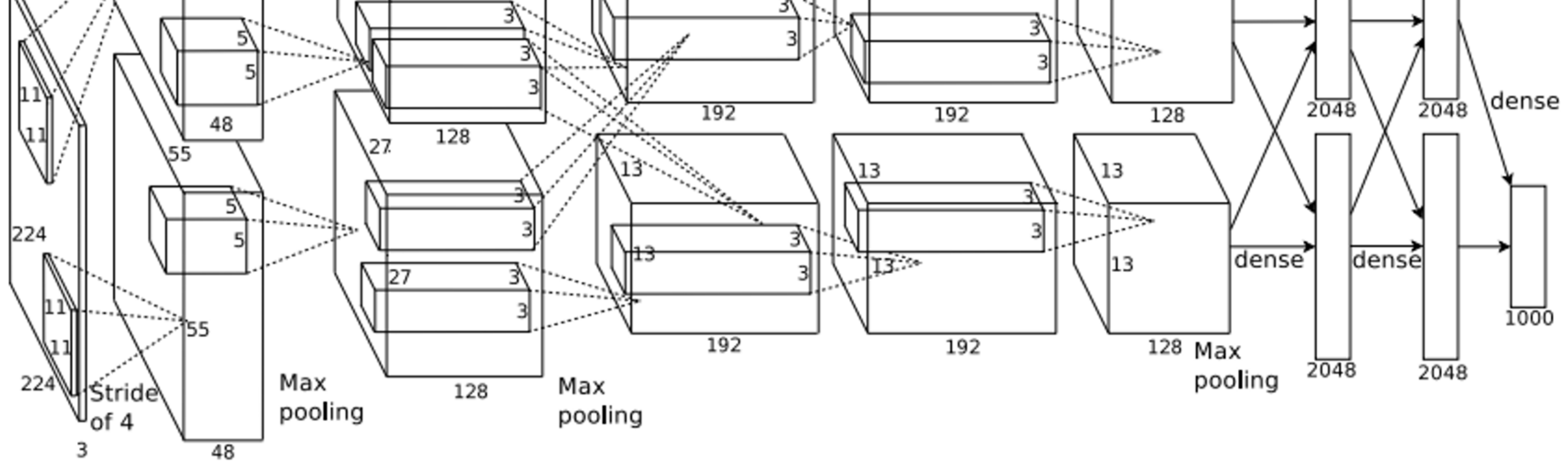
- 227 x 227 inputs
- 5 Convolutional Layers
- Max pooling
- 3 Fully-connected Layers
- ReLU nonlinearities

- Used “Local response normalization”; *Not used anymore*

- Trained on two GTX 580 GPUs - only 3GB of memory each! Model split over two GPUs.

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012.

AlexNet



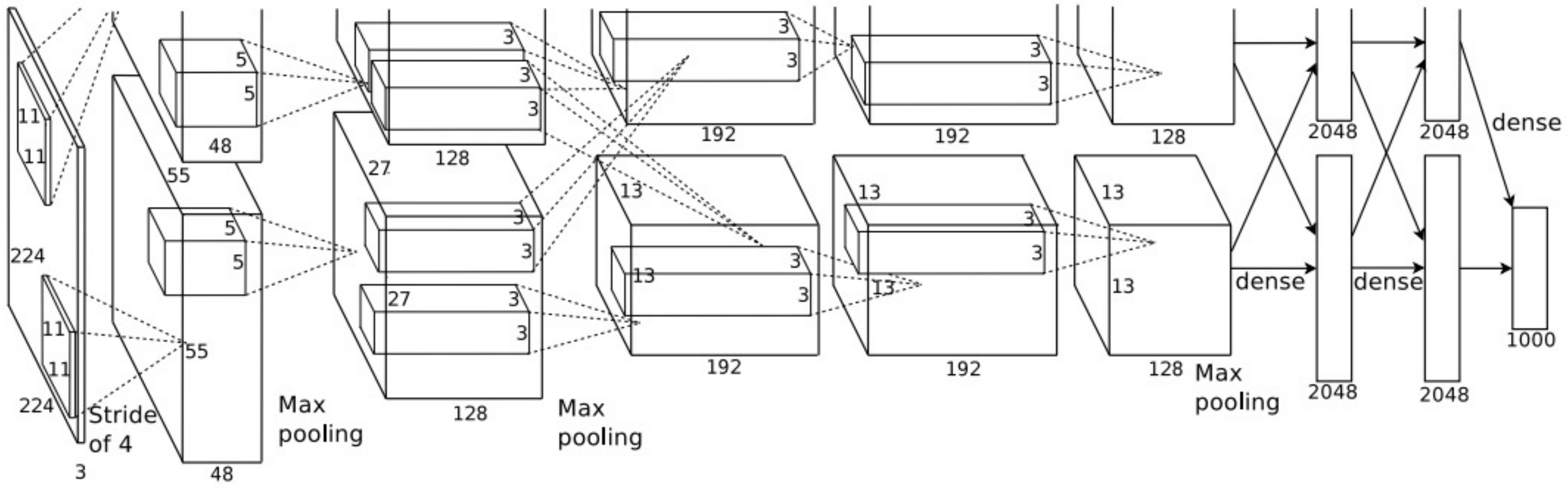
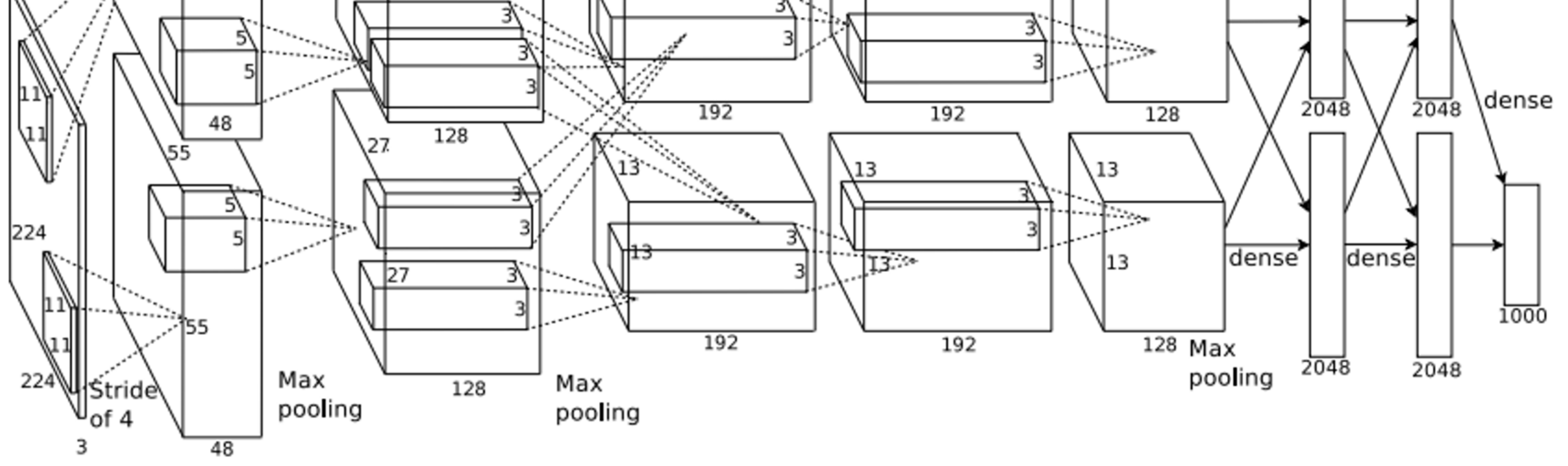


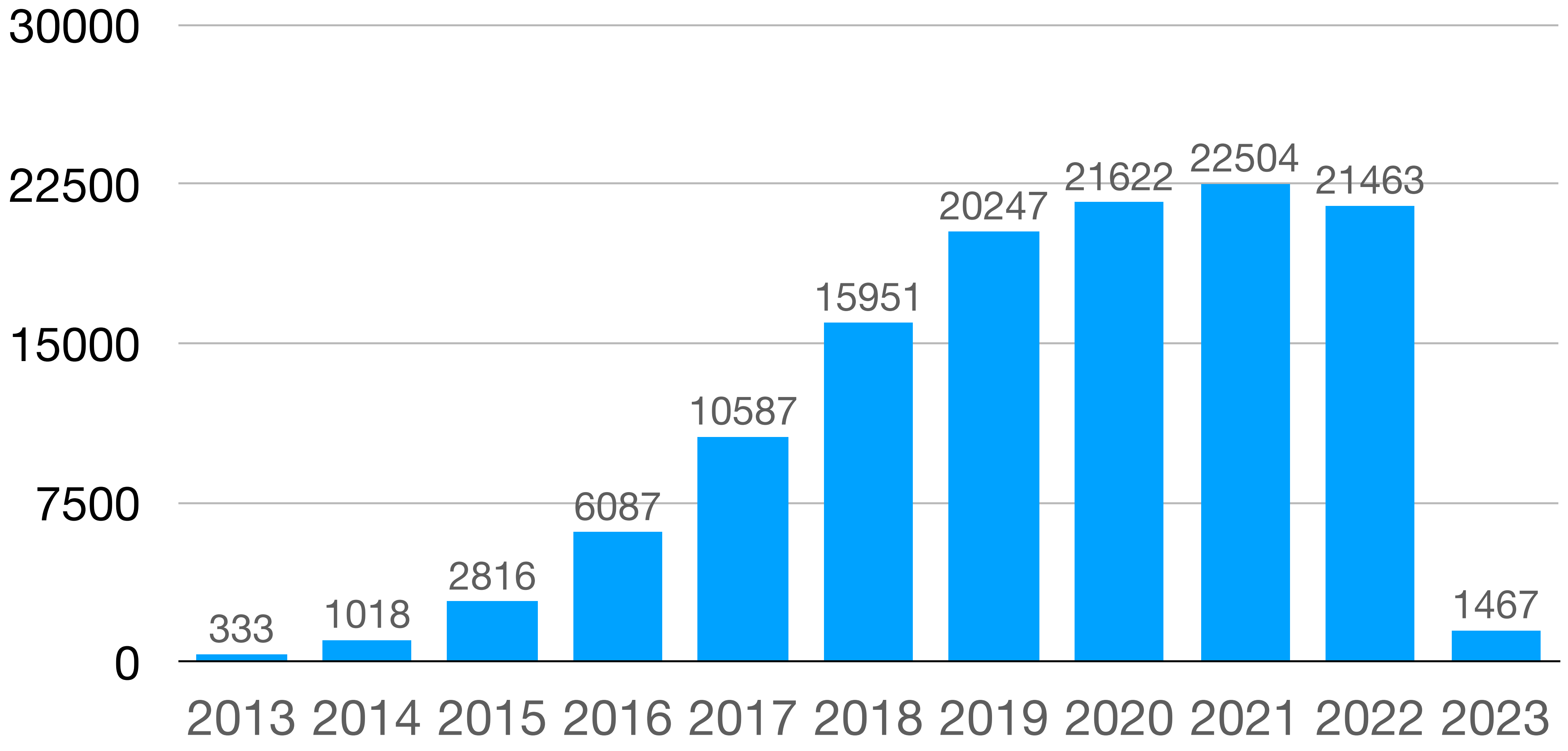
Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012.



AlexNet

AlexNet citations per year
(as of 1/31/2023)



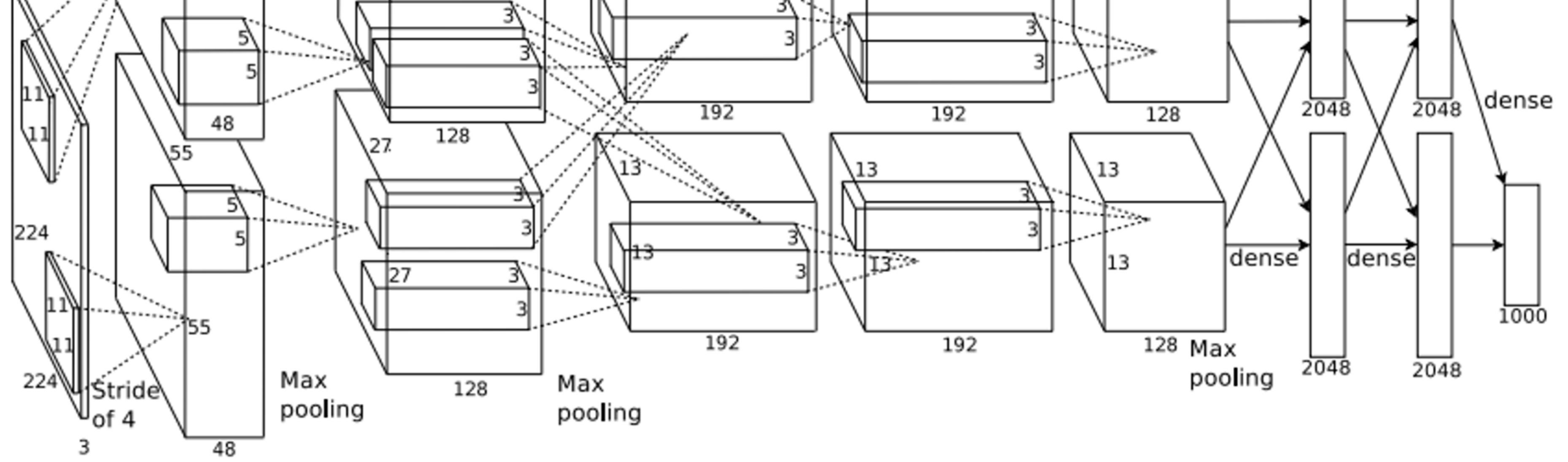
Total citations: **>120,000**

<u>Citation Counts:</u>

- Darwin, “On the origin of species”, 1859: **60,117**
- Shannon, “A mathematical theory of communication,” 1948: **140,459**
- Watson and Crick, “Molecular Structure of Nucleic Acids,” 1953: **16,298**

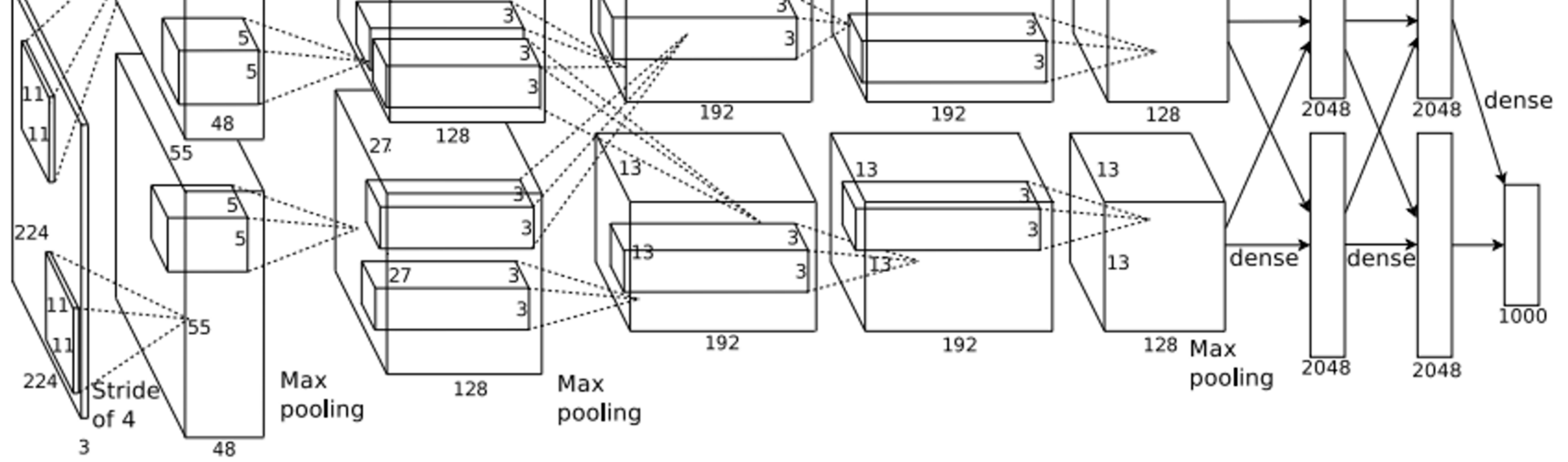
Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012.

AlexNet



	Input size		Layer				Output size	
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W
Conv1	3	227	64	11	4	2	?	

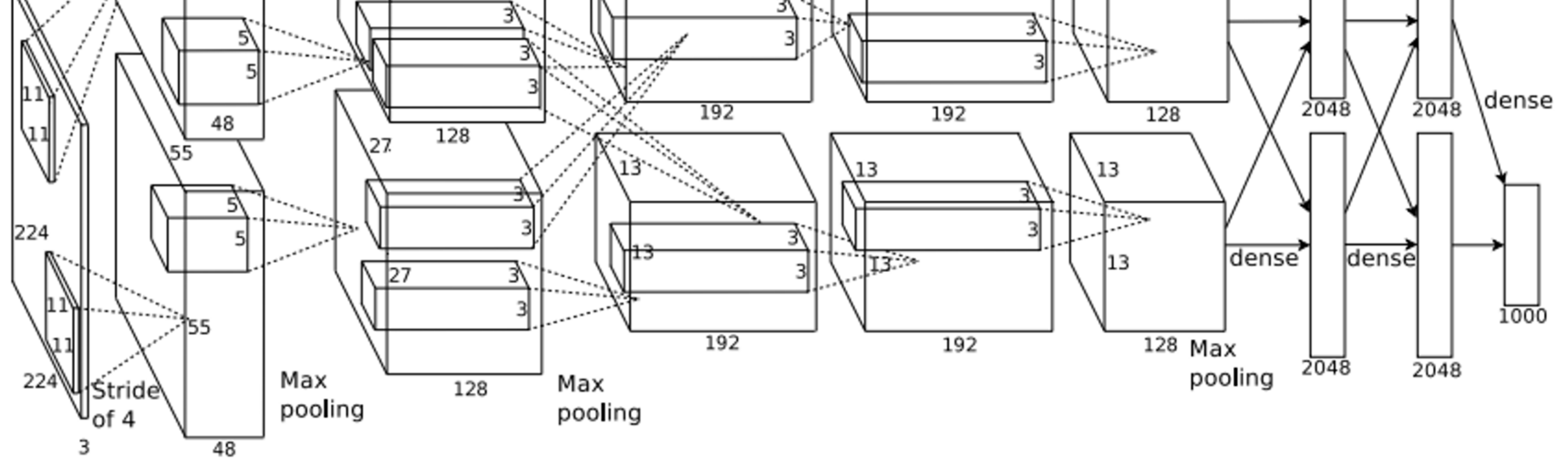
AlexNet



	Input size		Layer				Output size	
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W
Conv1	3	227	64	11	4	2	64	?

Recall: Output channels = number of filters

AlexNet



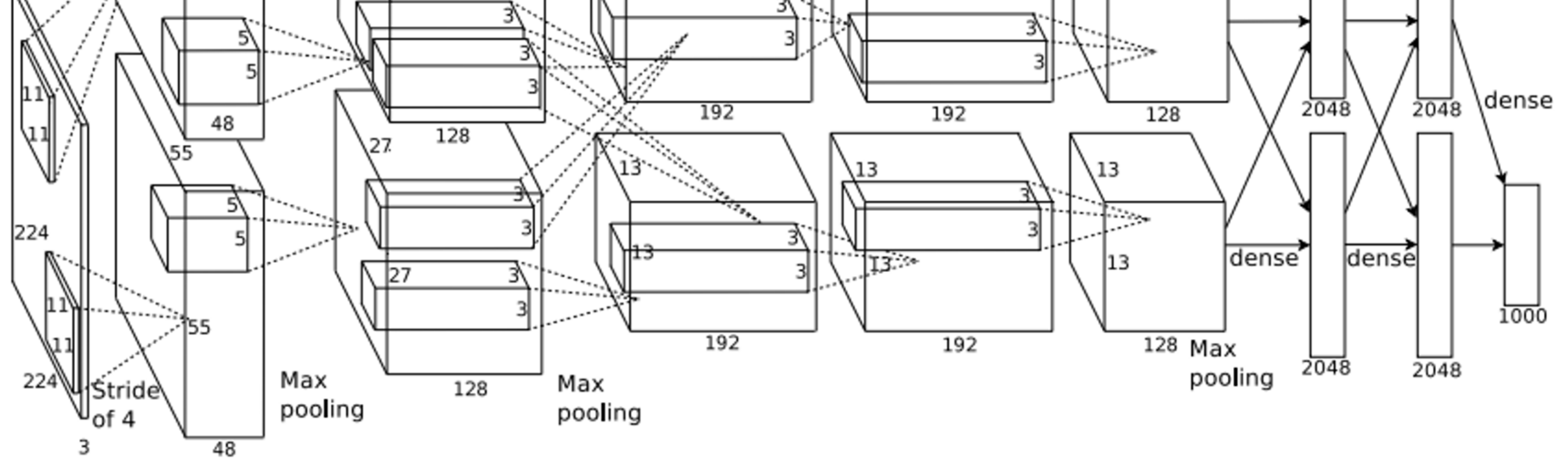
	Input size		Layer				Output size	
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W
Conv1	3	227	64	11	4	2	64	56

Recall: $W' = (W - K + 2P) / S + 1$

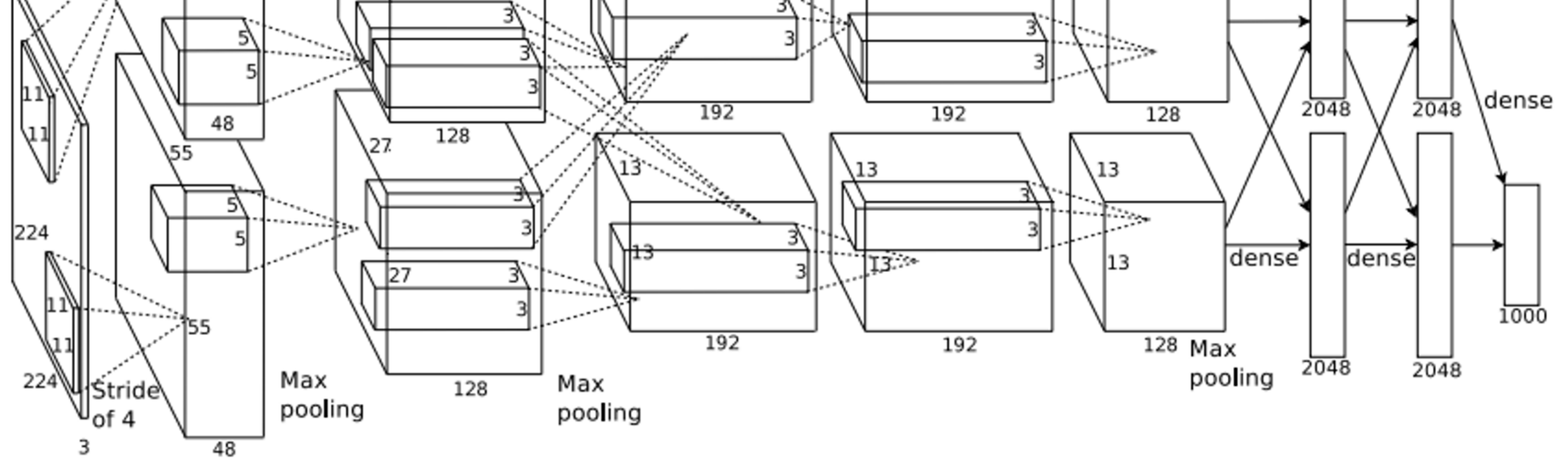
$= (227 - 11 + 2 \times 2) / 4 + 1$

$= 220/ 4 + 1 = 56$

AlexNet



	Input size		Layer				Output size		
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)
Conv1	3	227	64	11	4	2	64	56	?



AlexNet

	Input size		Layer				Output size		
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)
Conv1	3	227	64	11	4	2	64	56	784

Number of output elements = C x H’ x W’

= 64 x 56 x 56 = 200,704

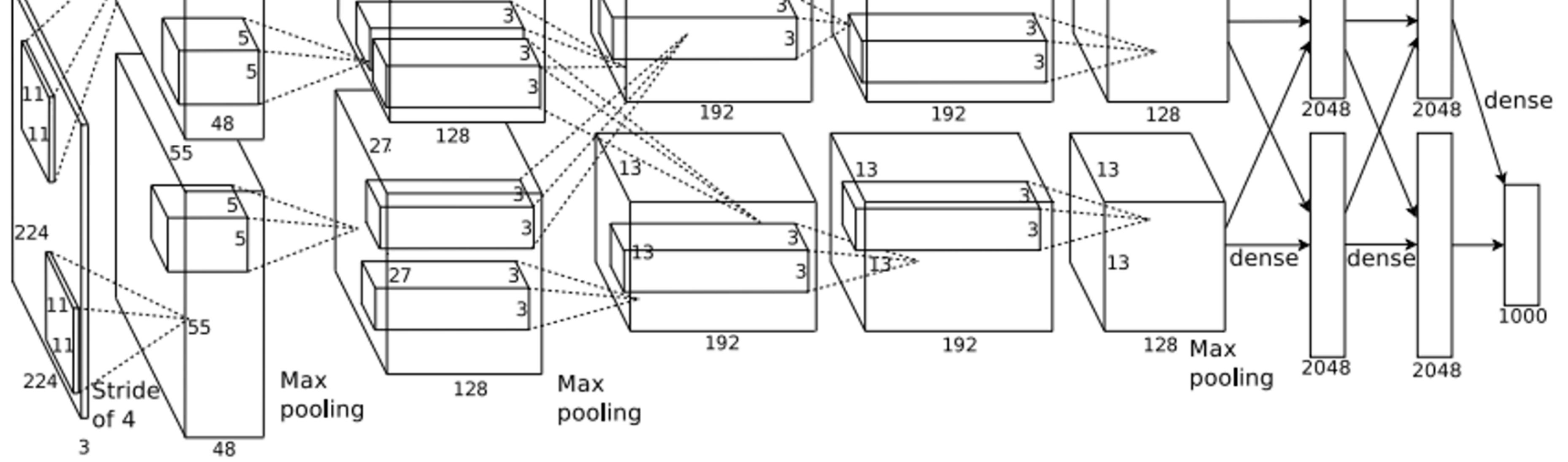
Bytes per element = 4 (for 32-bit floating point)

KB = (number of elements) x (bytes per elem) /1024

= 200704 x 4 / 1024

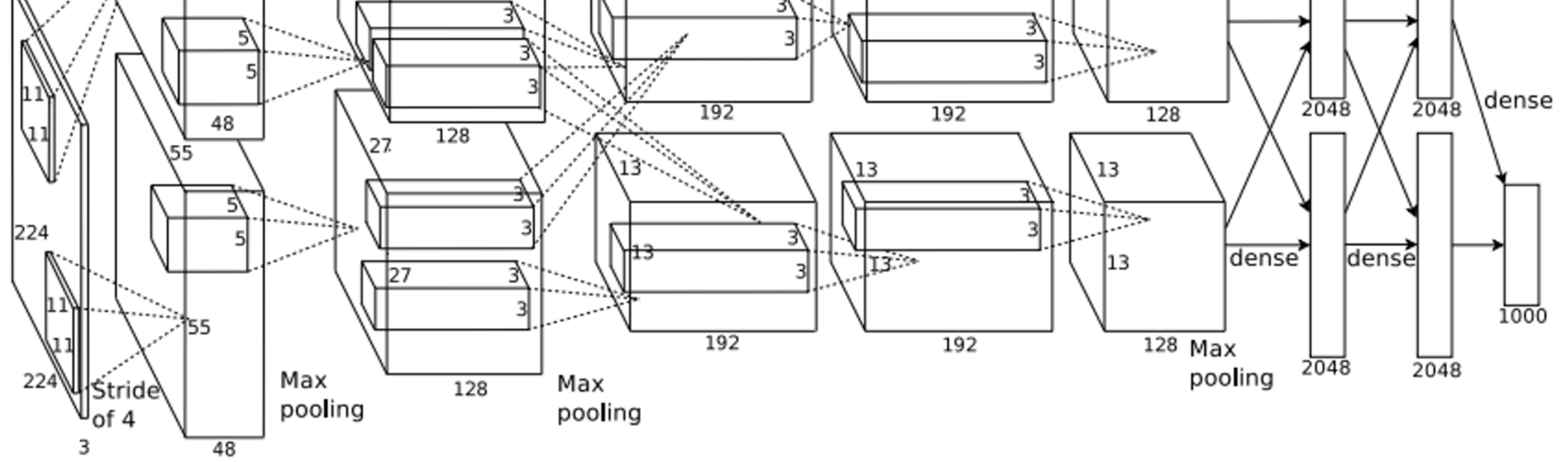
= **784**

AlexNet



	Input size		Layer				Output size			
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)
Conv1	3	227	64	11	4	2	64	56	784	?

AlexNet



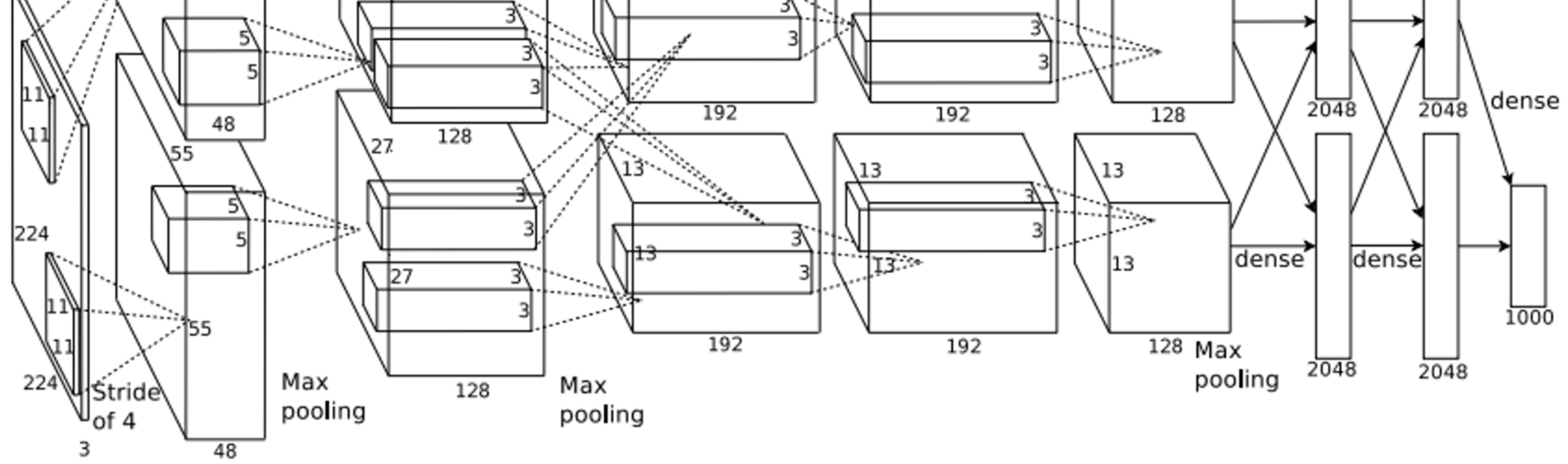
	Input size		Layer				Output size			
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)
Conv1	3	227	64	11	4	2	64	56	784	23

Weight shape $= C_{out} \times C_{in} \times K \times K$
$= 64 \times 3 \times 11 \times 11$

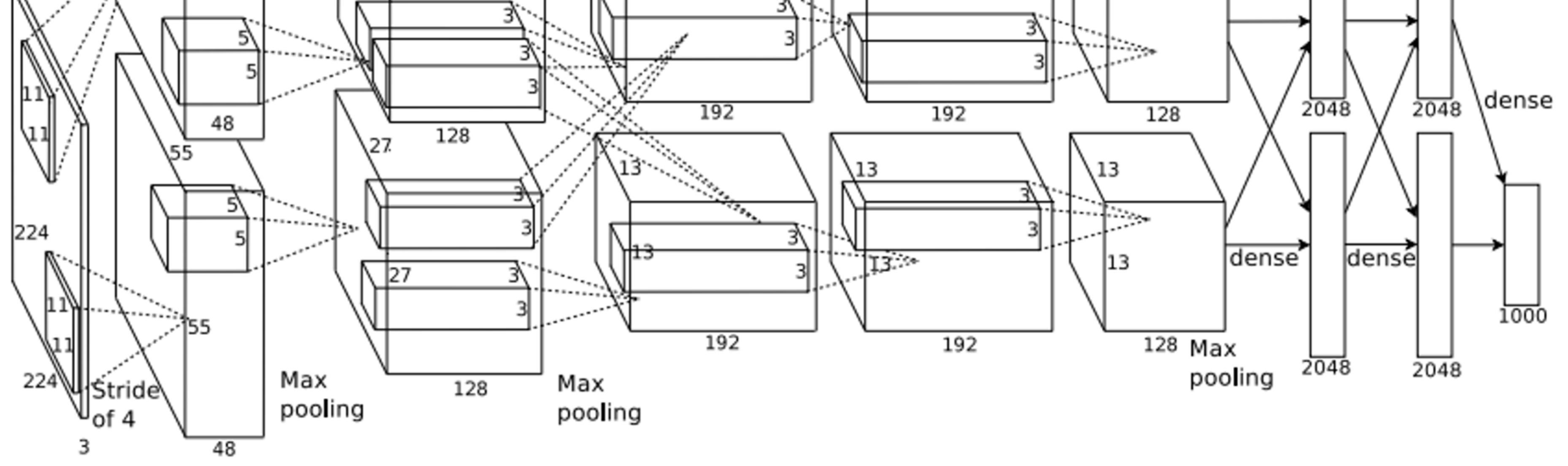
Bias shape $= C_{out} = 64$

Number of weights $= 64 \times 3 \times 11 \times 11 + 64$
$=$ **23,296**

AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	?

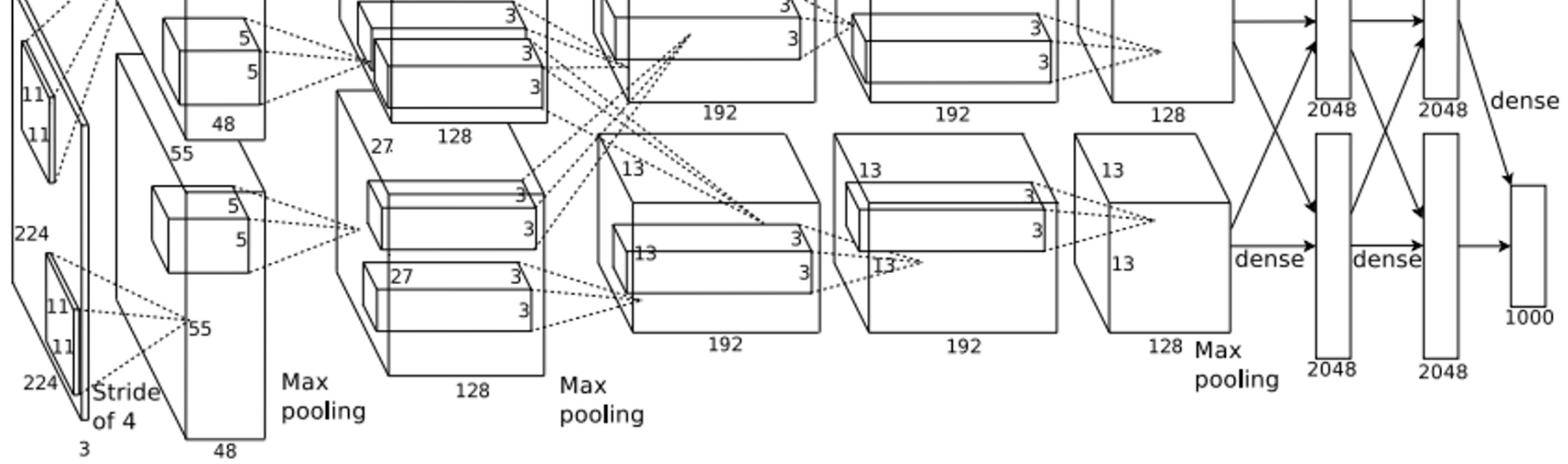


AlexNet

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73

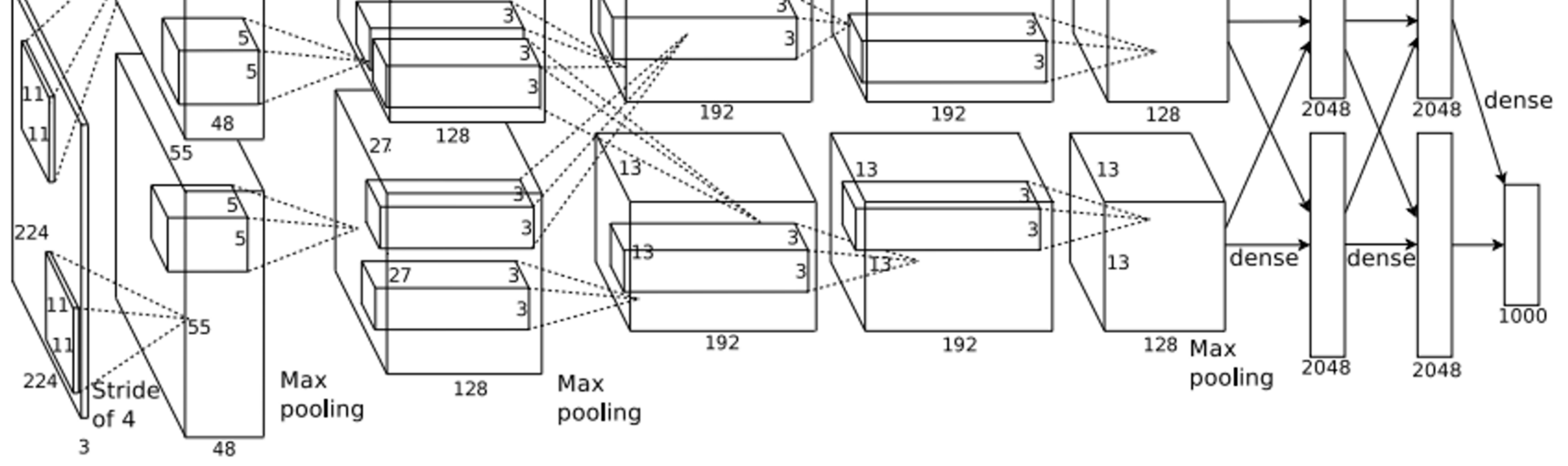
Number of floating point operations (multiply + add)
= (number of output elements) * (ops per output elem)
= $(C_{out} \times H' \times W') * (C_{in} \times K \times K)$
= (64 * 56 * 56) * (3 * 11 * 11)
= 200,704 * 363
= **72,855,552**

AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	?				

AlexNet



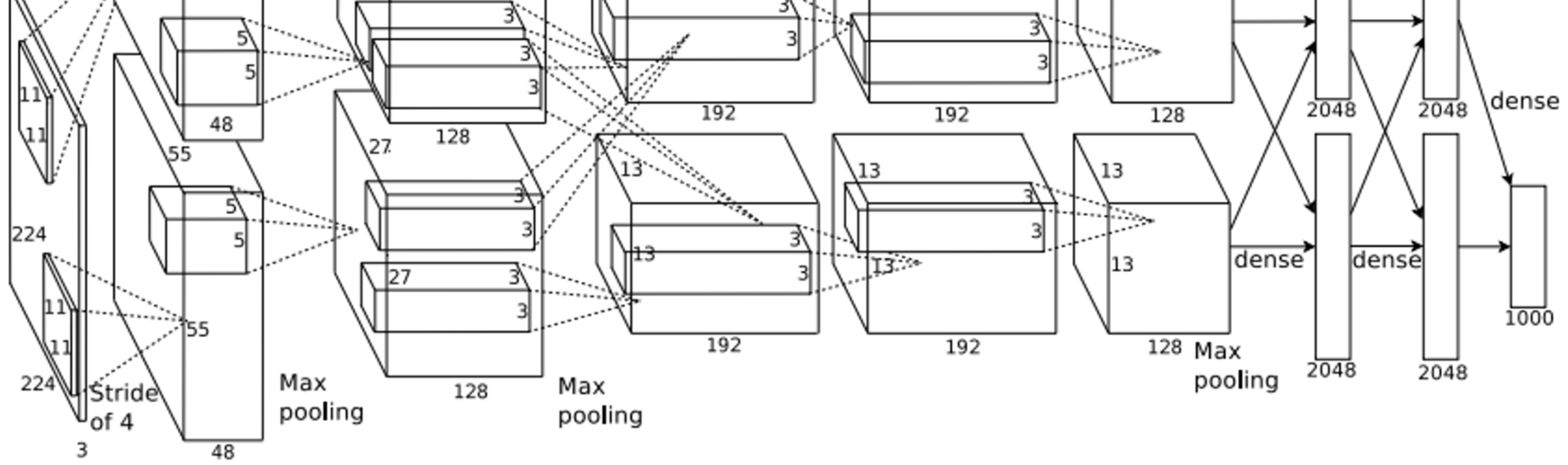
	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27			

For pooling layer:

#output channels = #input channels = 64

$$W' = \text{floor}((W-K)/S+1)$$
$$= \text{floor}(53/2 + 1) = \text{floor}(27.5) = \mathbf{27}$$

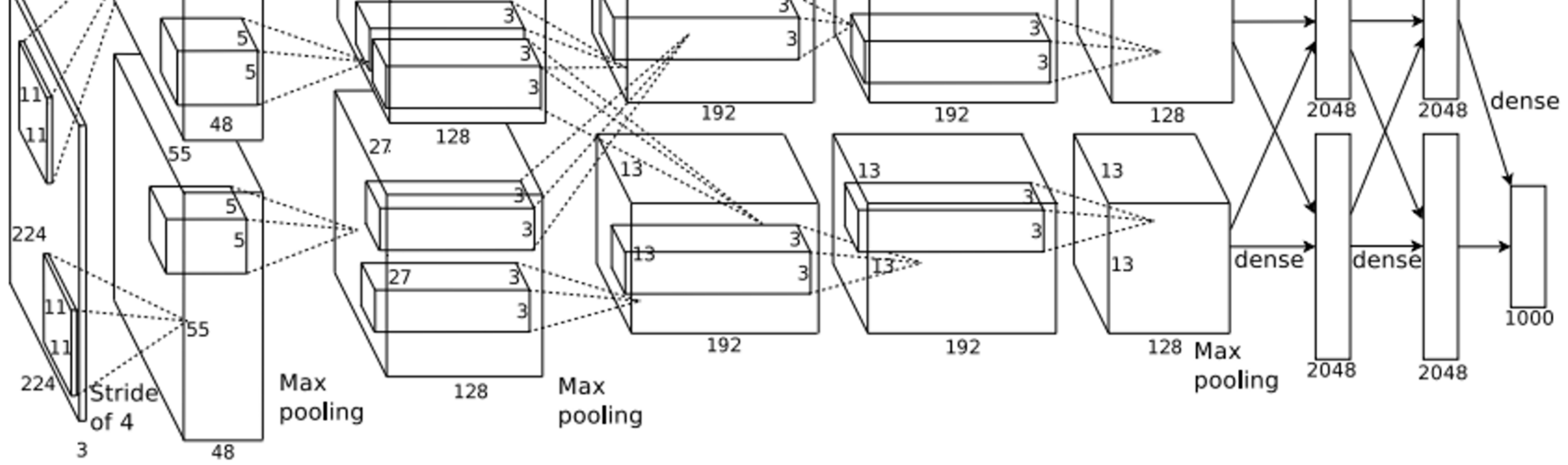
AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	?	

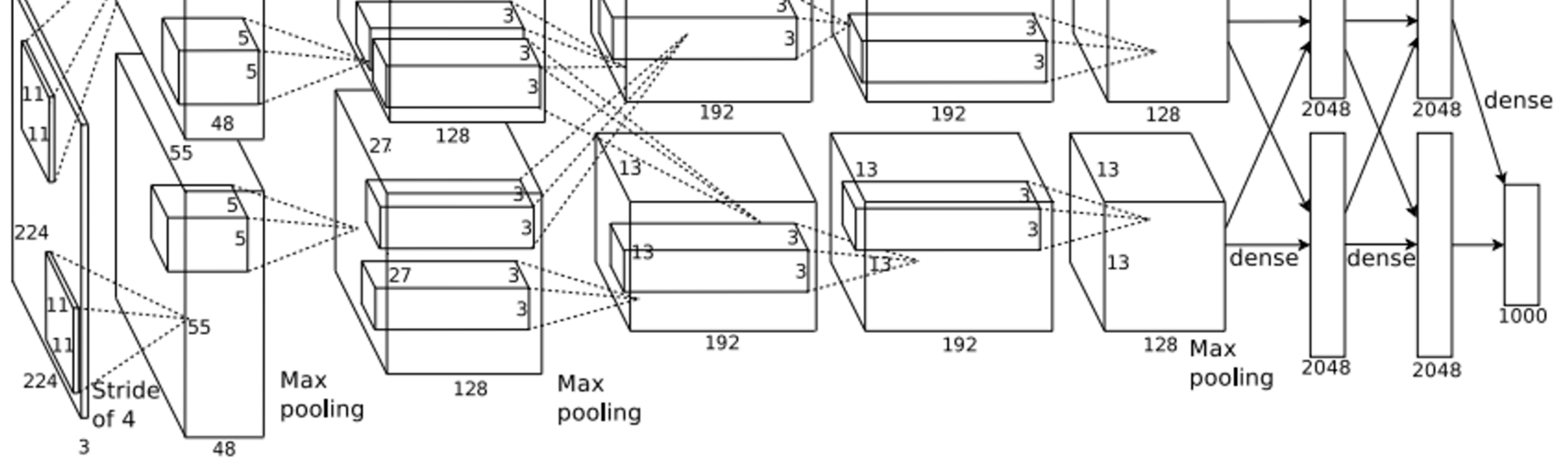
#output elms = C_{out} x H' x W'
Bytes per elem = 4
KB = C_{out} x H' x W' x 4 / 1024
= 64 * 27 * 27 * 4 / 1024
= **182.25**

AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0

Pooling layers have no learnable parameters!

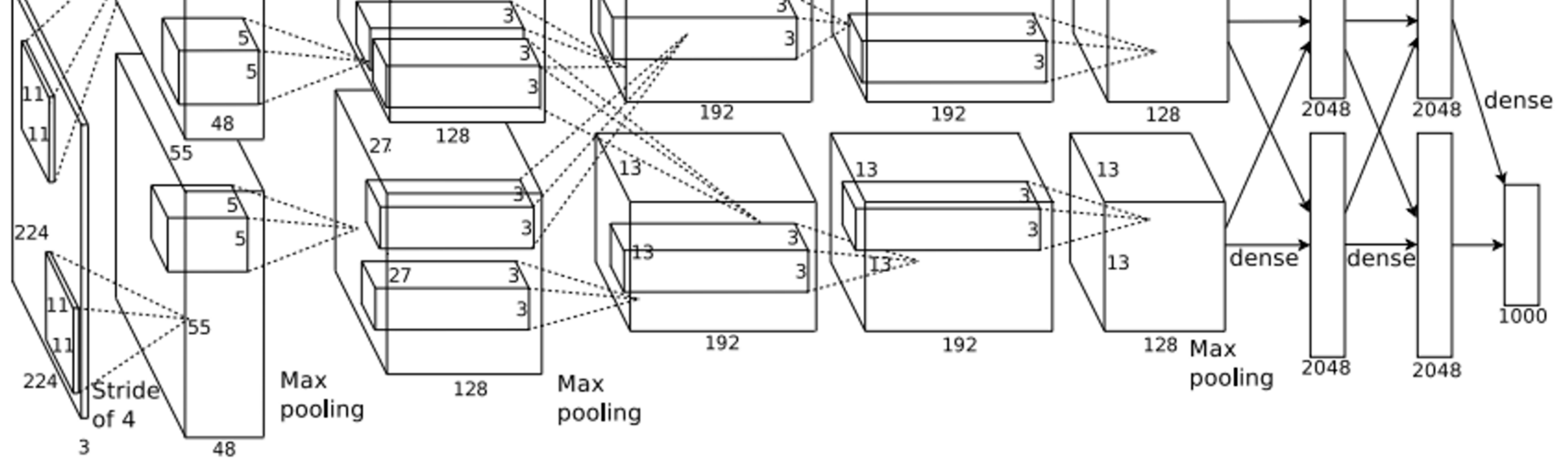


AlexNet

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0

Floating-point ops for pooling layer
= (numer of output positions) * (flops per output position)
= (C_{out} x H’ x W’) x (K x K)
= (64 * 27 * 27) * (3 * 3)
= 419,904
= **0.4 MFLOP**

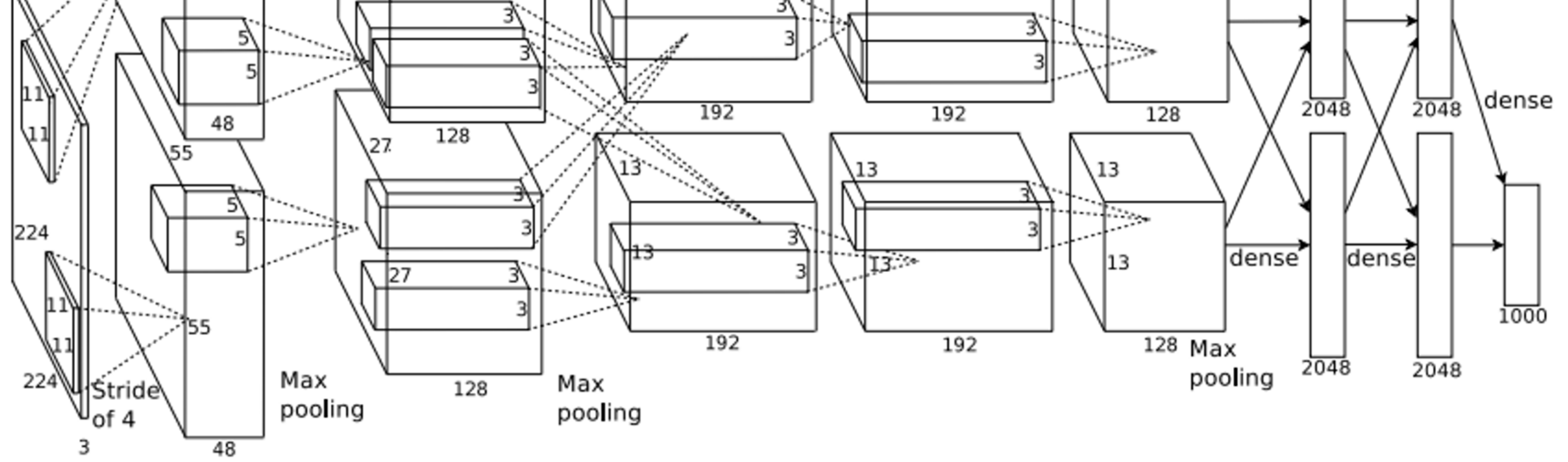
AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0
Conv2	64	27	192	5	1	2	192	27	547	307	224
Pool2	192	27		3	2	0	192	13	127	0	0
Conv3	192	13	384	3	1	1	384	13	254	664	112
Conv4	384	13	256	3	1	1	256	13	169	885	145
Conv5	256	13	256	3	1	1	256	13	169	590	100
Pool5	256	13		3	2	0	256	6	36	0	0
Flatten	256	6					9216		36	0	0

Flatten output size = C_{in} x H x W
= 256 * 6 * 6
= **9216**

AlexNet

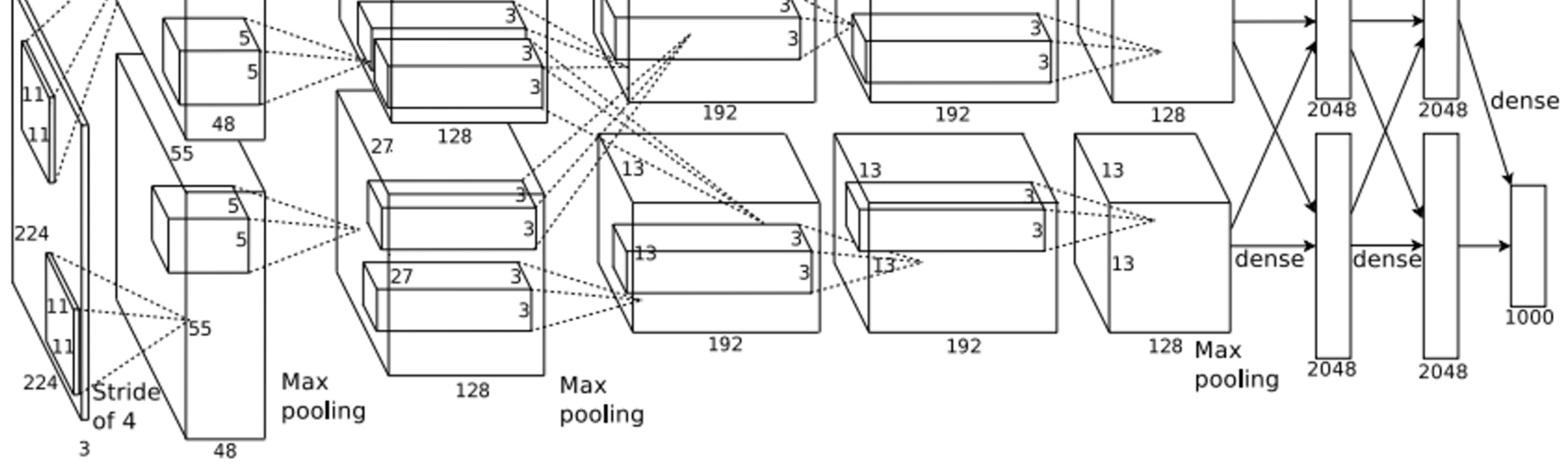


	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0
Conv2	64	27	192	5	1	2	192	27	547	307	224
Pool2	192	27		3	2	0	192	13	127	0	0
Conv3	192	13	384	3	1	1	384	13	254	664	112
Conv4	384	13	256	3	1	1	256	13	169	885	145
Conv5	256	13	256	3	1	1	256	13	169	590	100
Pool5	256	13		3	2	0	256	6	36	0	0
Flatten	256	6					9216		36	0	0
FC6	9216		4096				4096		16	37749	38

FC params $= C_{in} * C_{out} + C_{out}$
$= 9216 * 4096 + 4096$
$= 37,725,832$

FC flops $= C_{in} * C_{out}$
$= 9216 * 4096$
$= 37,748,736$

AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
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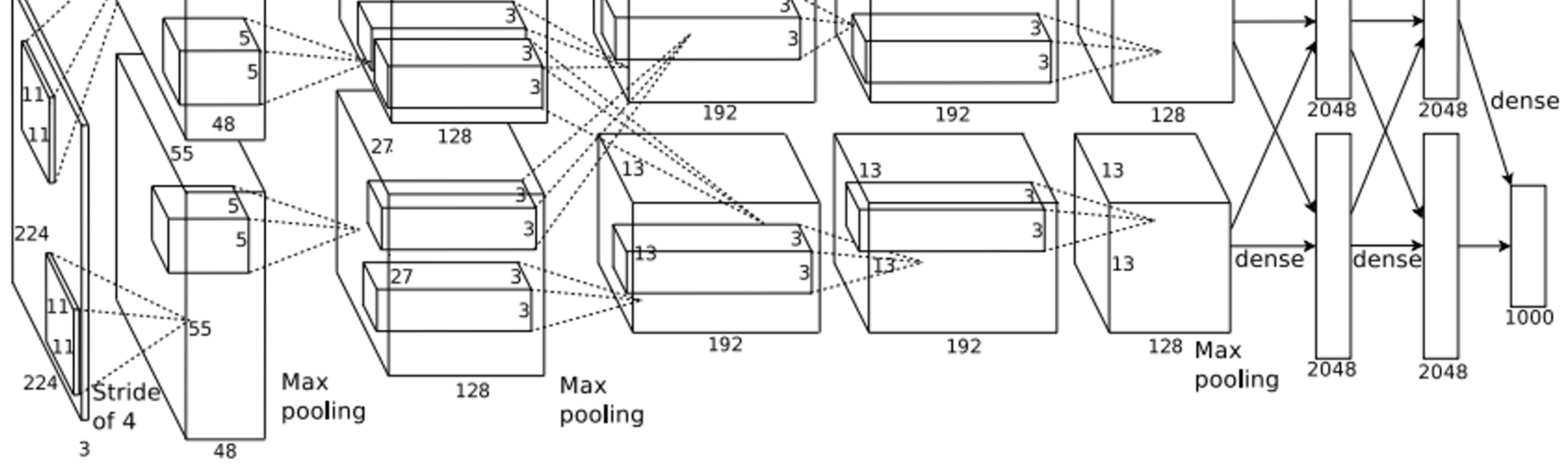
Pool1	64	56		3	2	0	64	27	182	0	0
Conv2	64	27	192	5	1	2	192	27	547	307	224
Pool2	192	27		3	2	0	192	13	127	0	0
Conv3	192	13	384	3	1	1	384	13	254	664	112
Conv4	384	13	256	3	1	1	256	13	169	885	145
Conv5	256	13	256	3	1	1	256	13	169	590	100
Pool5	256	13		3	2	0	256	6	36	0	0
Flatten	256	6					9216		36	0	0
FC6	9216		4096				4096		16	37749	38
FC7	4096		4096				4096		16	16777	17
FC8	4096		1000				1000		4	4096	4

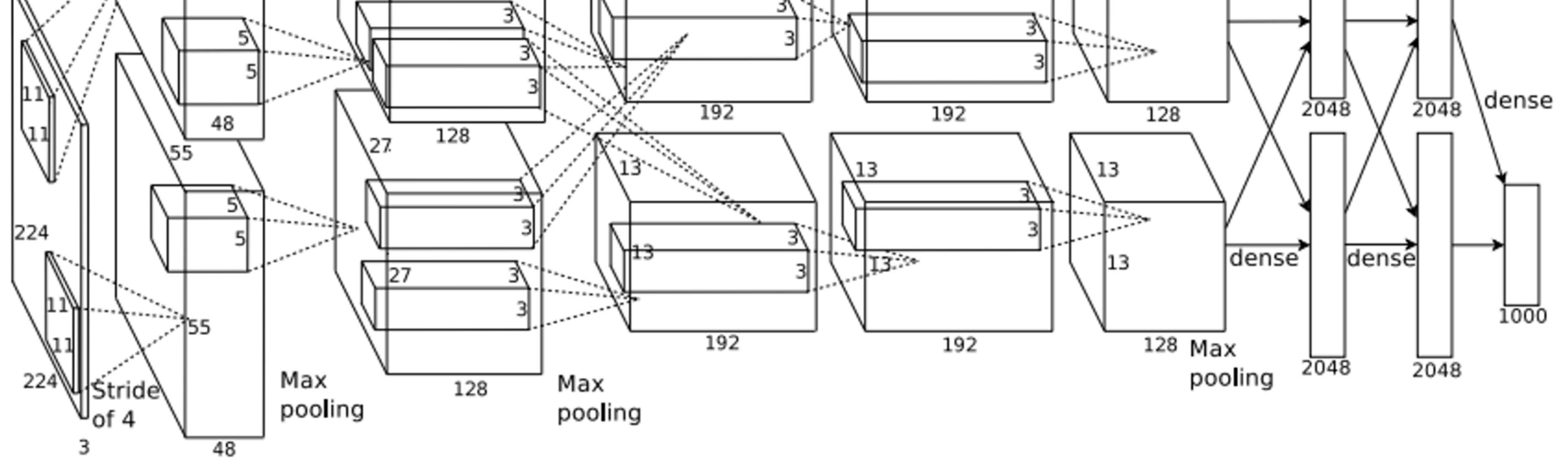
AlexNet



How to choose this? Trial and error :(

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
Conv1	3	227	64	11	4	2	64	56	784	23	73
Pool1	64	56		3	2	0	64	27	182	0	0
Conv2	64	27	192	5	1	2	192	27	547	307	224
Pool2	192	27		3	2	0	192	13	127	0	0
Conv3	192	13	384	3	1	1	384	13	254	664	112
Conv4	384	13	256	3	1	1	256	13	169	885	145
Conv5	256	13	256	3	1	1	256	13	169	590	100
Pool5	256	13		3	2	0	256	6	36	0	0
Flatten	256	6					9216		36	0	0
FC6	9216		4096				4096		16	37749	38
FC7	4096		4096				4096		16	16777	17
FC8	4096		1000				1000		4	4096	4

AlexNet



	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params (k)	Flop (M)
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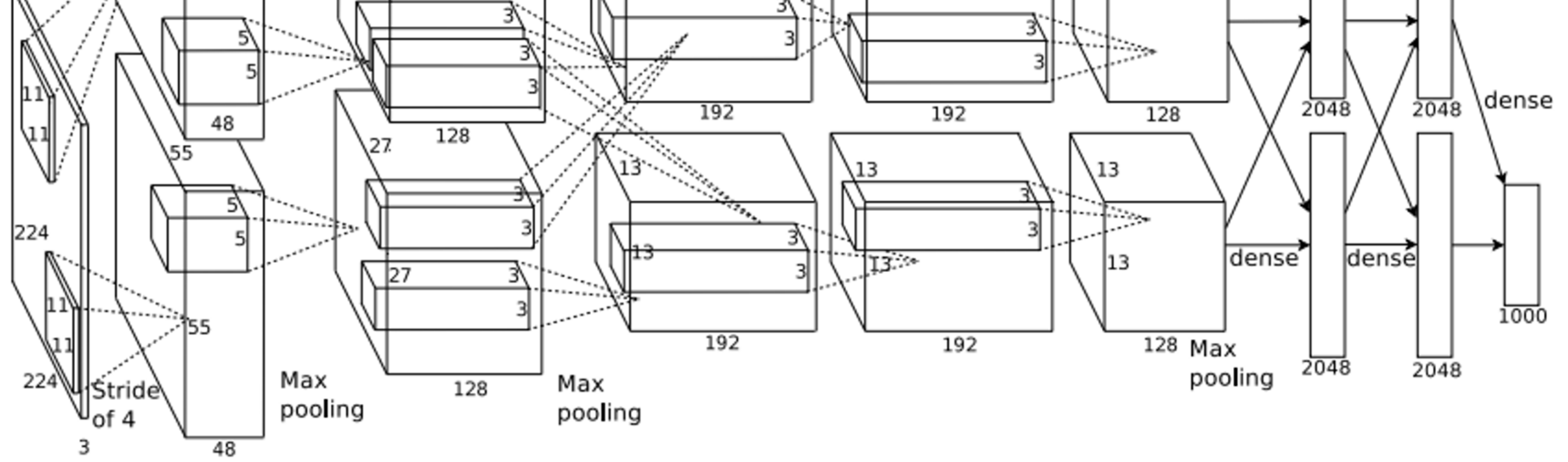
Pool2	192	27		3	2	0	192	13	127	0	0
Conv3	192	13	384	3	1	1	384	13	254	664	112
Conv4	384	13	256	3	1	1	256	13	169	885	145
Conv5	256	13	256	3	1	1	256	13	169	590	100
Pool5	256	13		3	2	0	256	6	36	0	0
Flatten	256	6					9216		36	0	0
FC6	9216		4096				4096		16	37749	38
FC7	4096		4096				4096		16	16777	17
FC8	4096		1000				1000		4	4096	4

Interesting trends here!

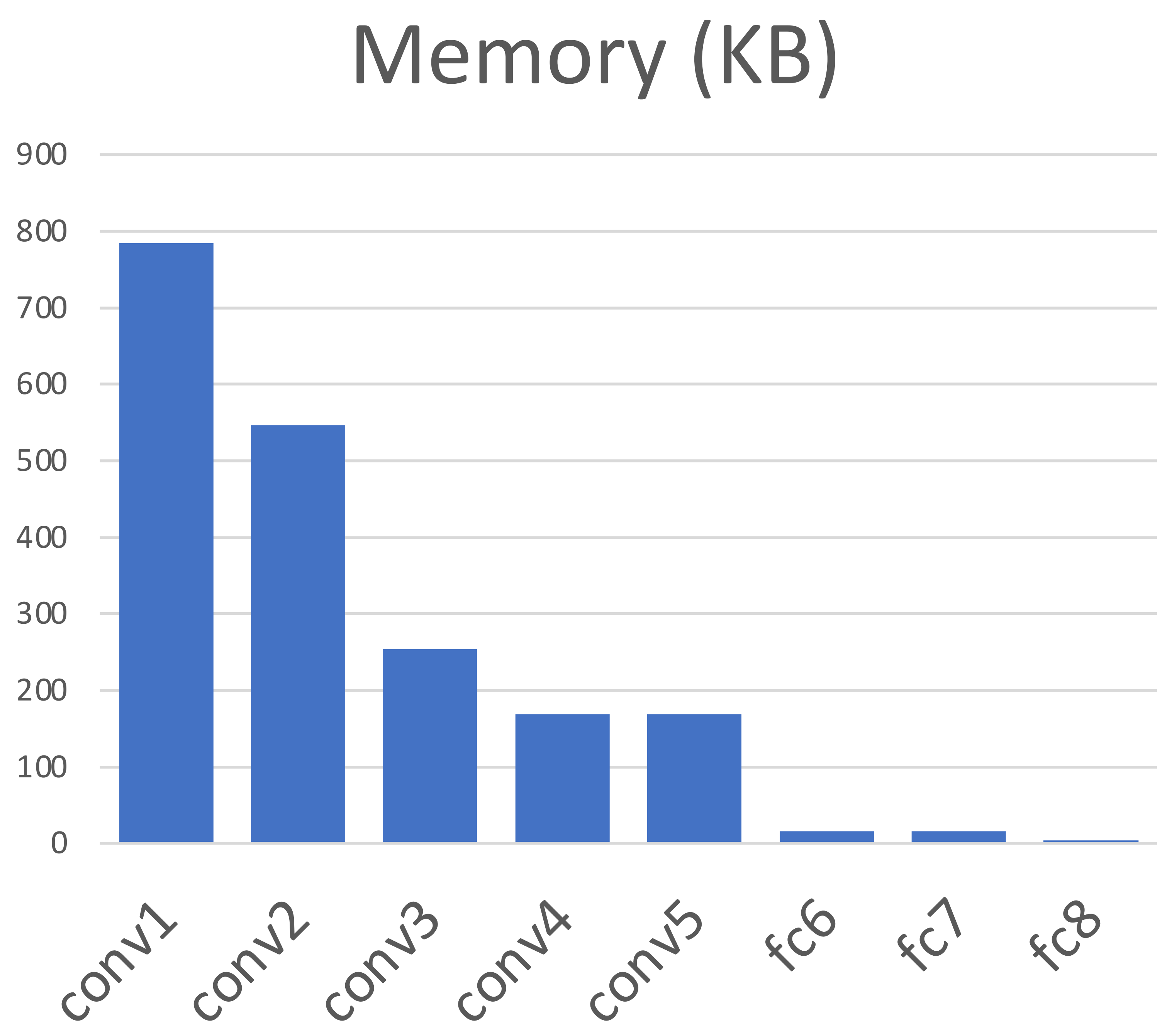
AlexNet

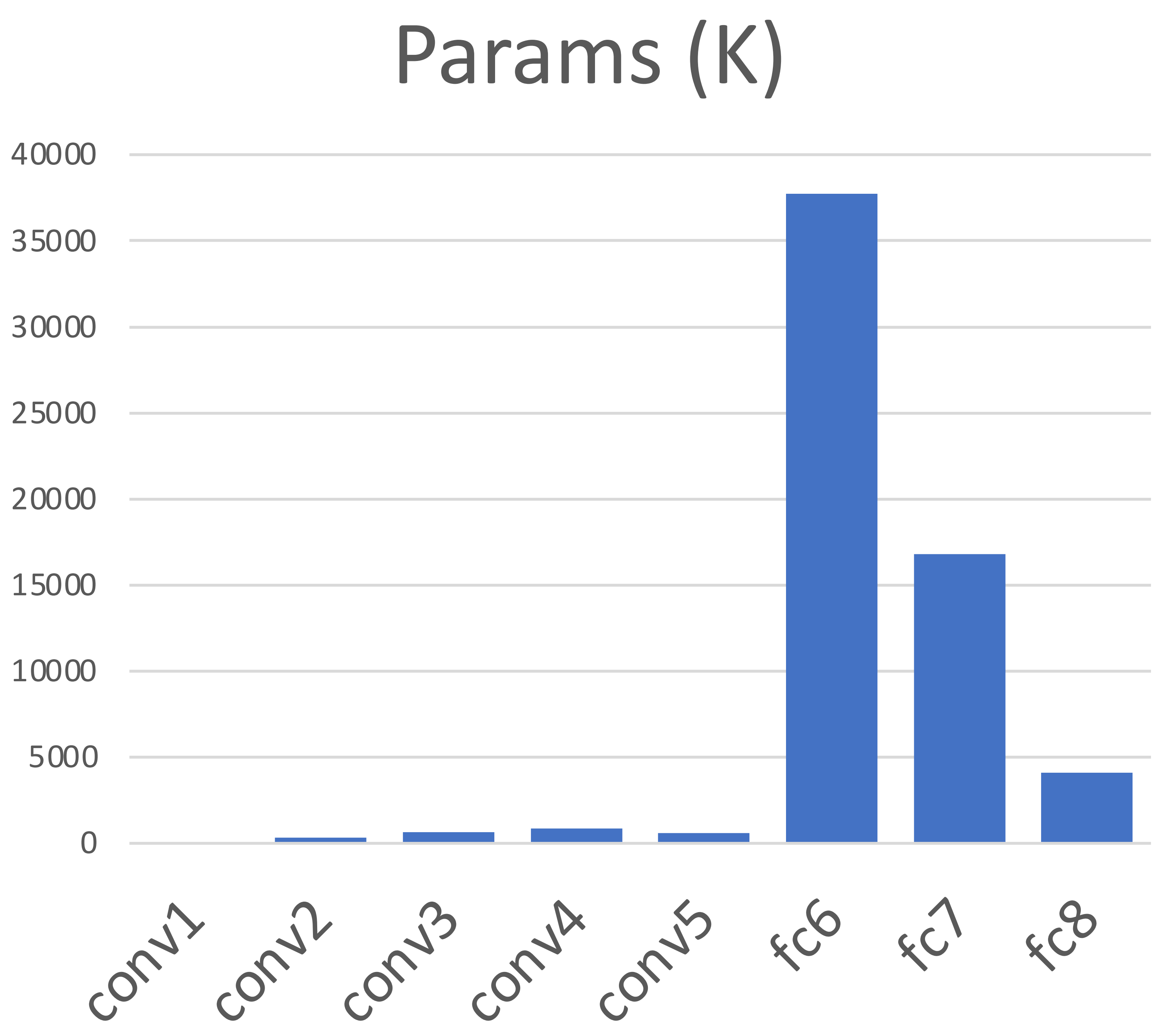


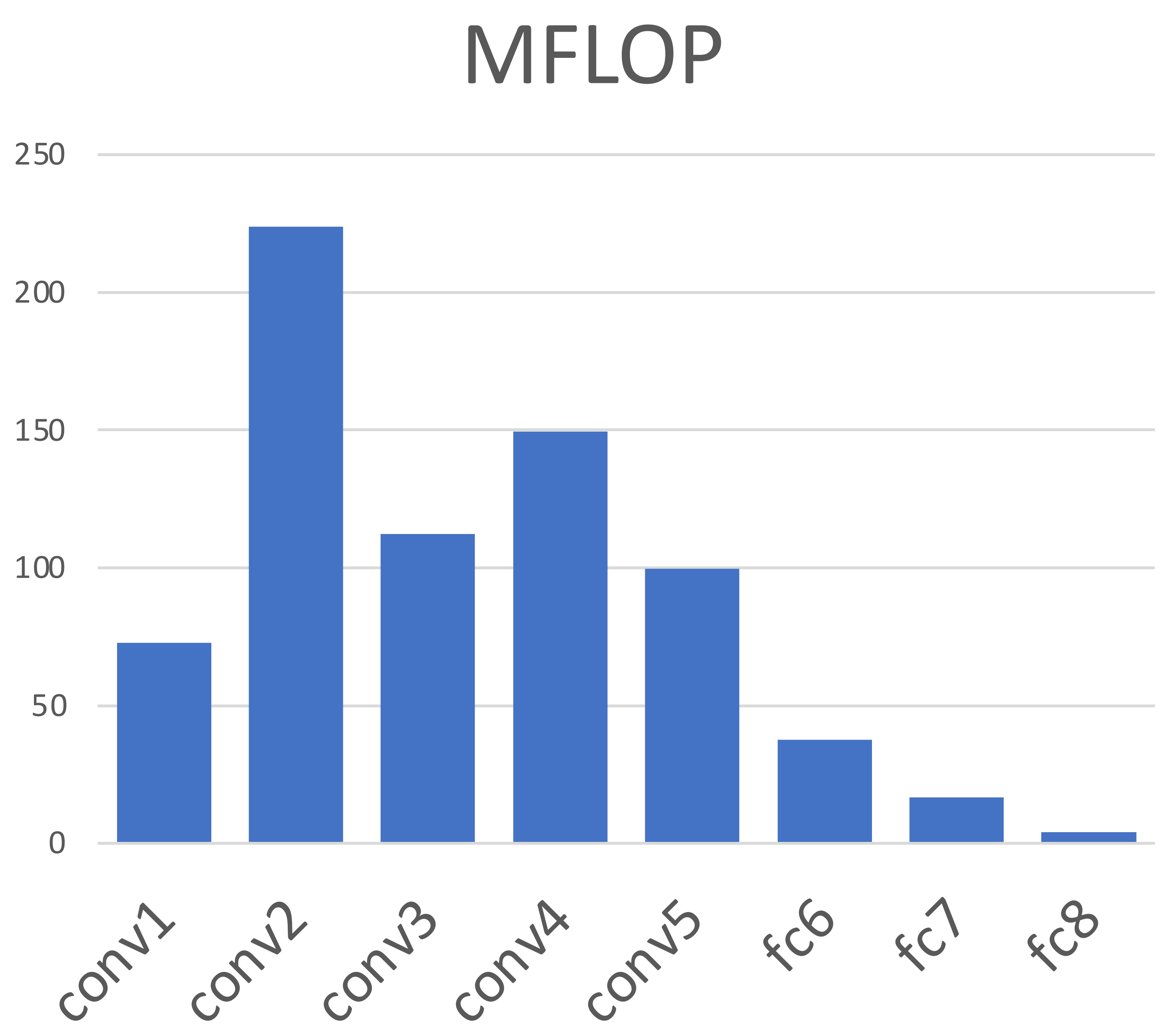
Most of the **memory usage** in the early convolution layers

Nearly all **parameters** are in the fully-connected layers

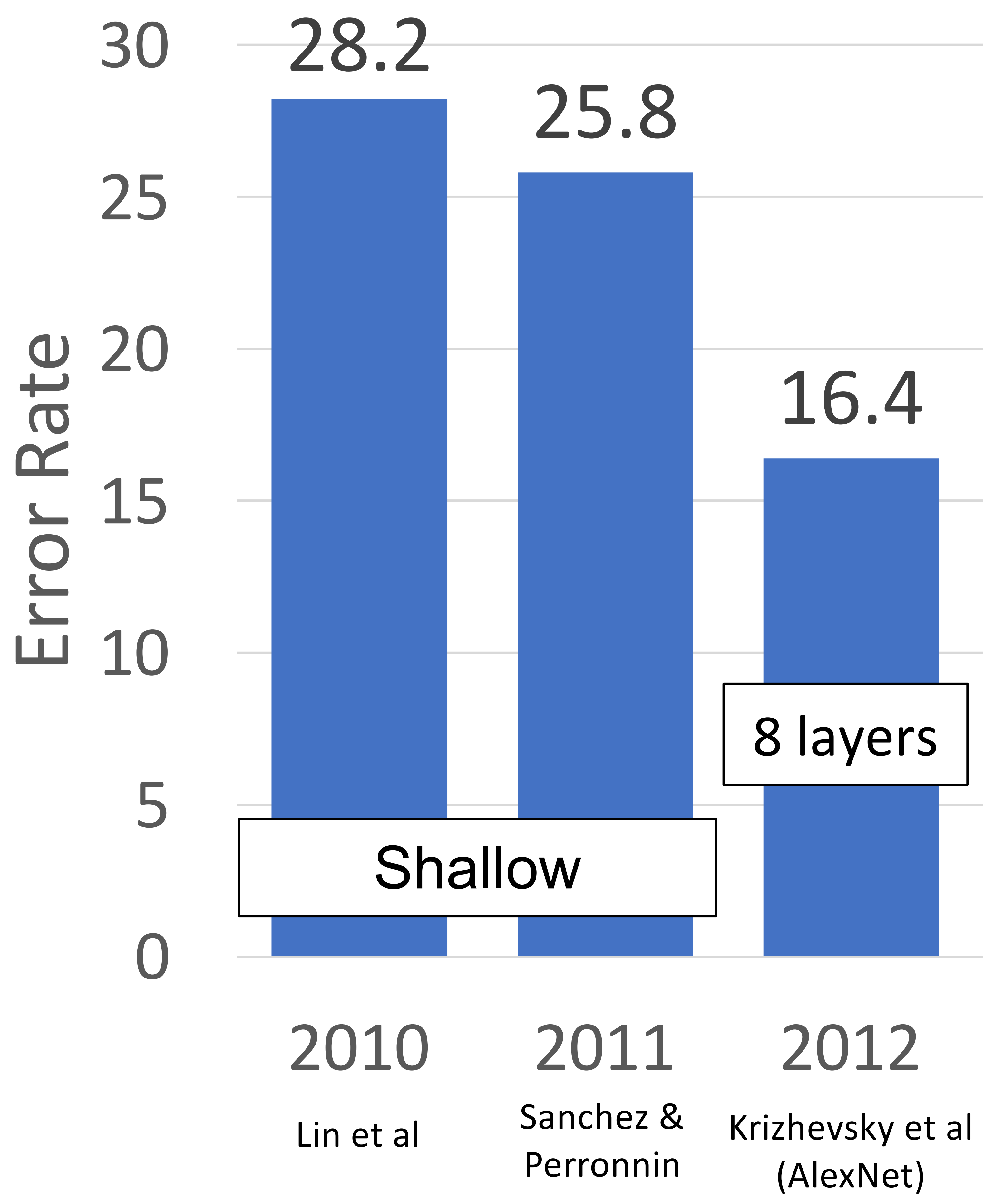
Most **floating-point ops** occur in the convolution layers



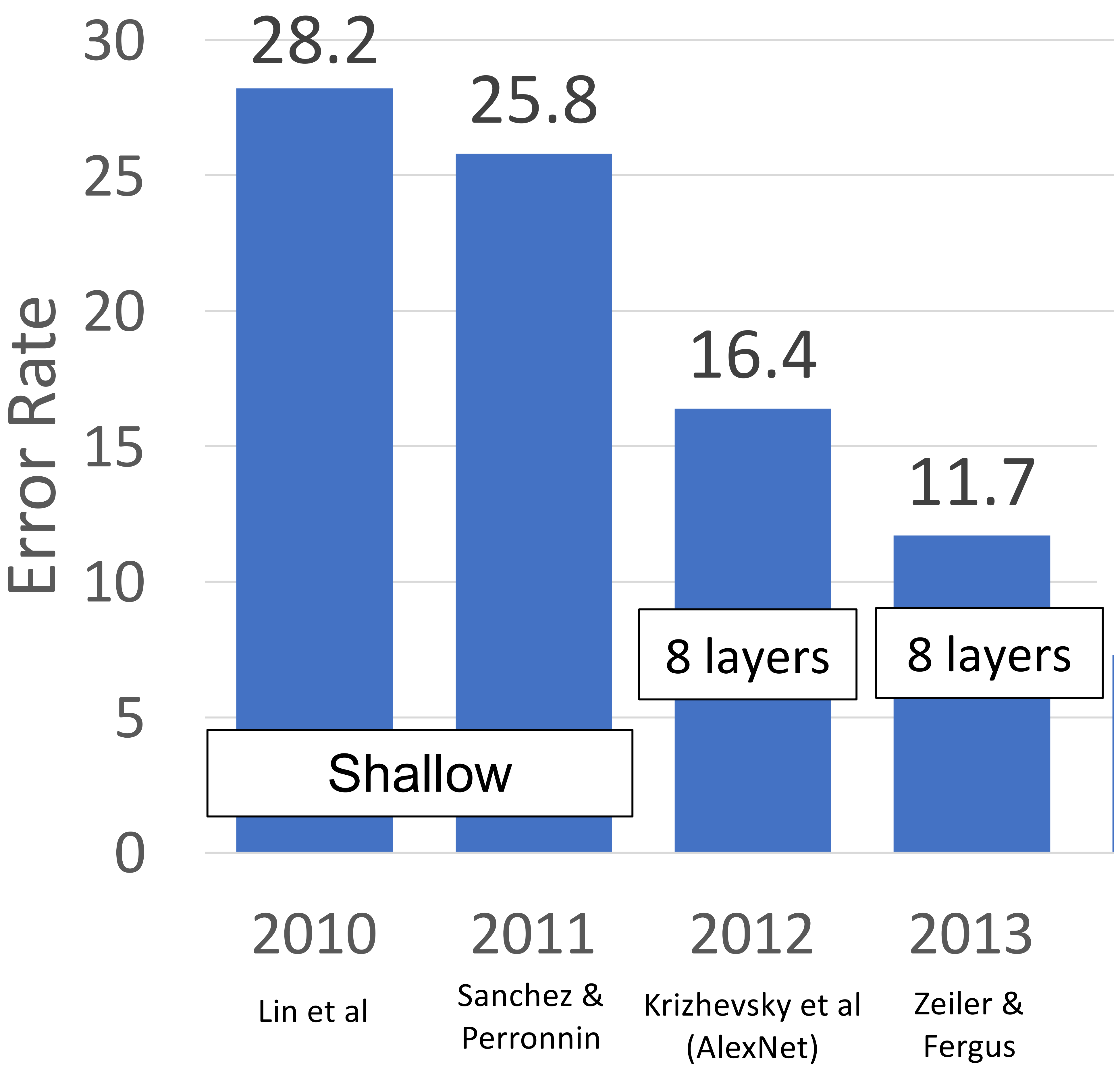




ImageNet Classification Challenge

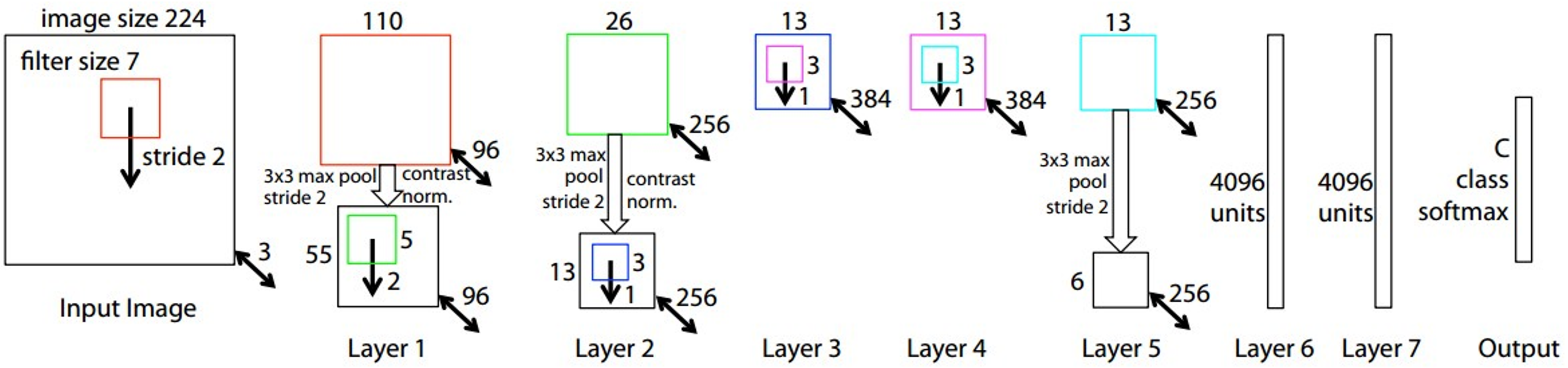


ImageNet Classification Challenge



ZFNet: A Bigger AlexNet

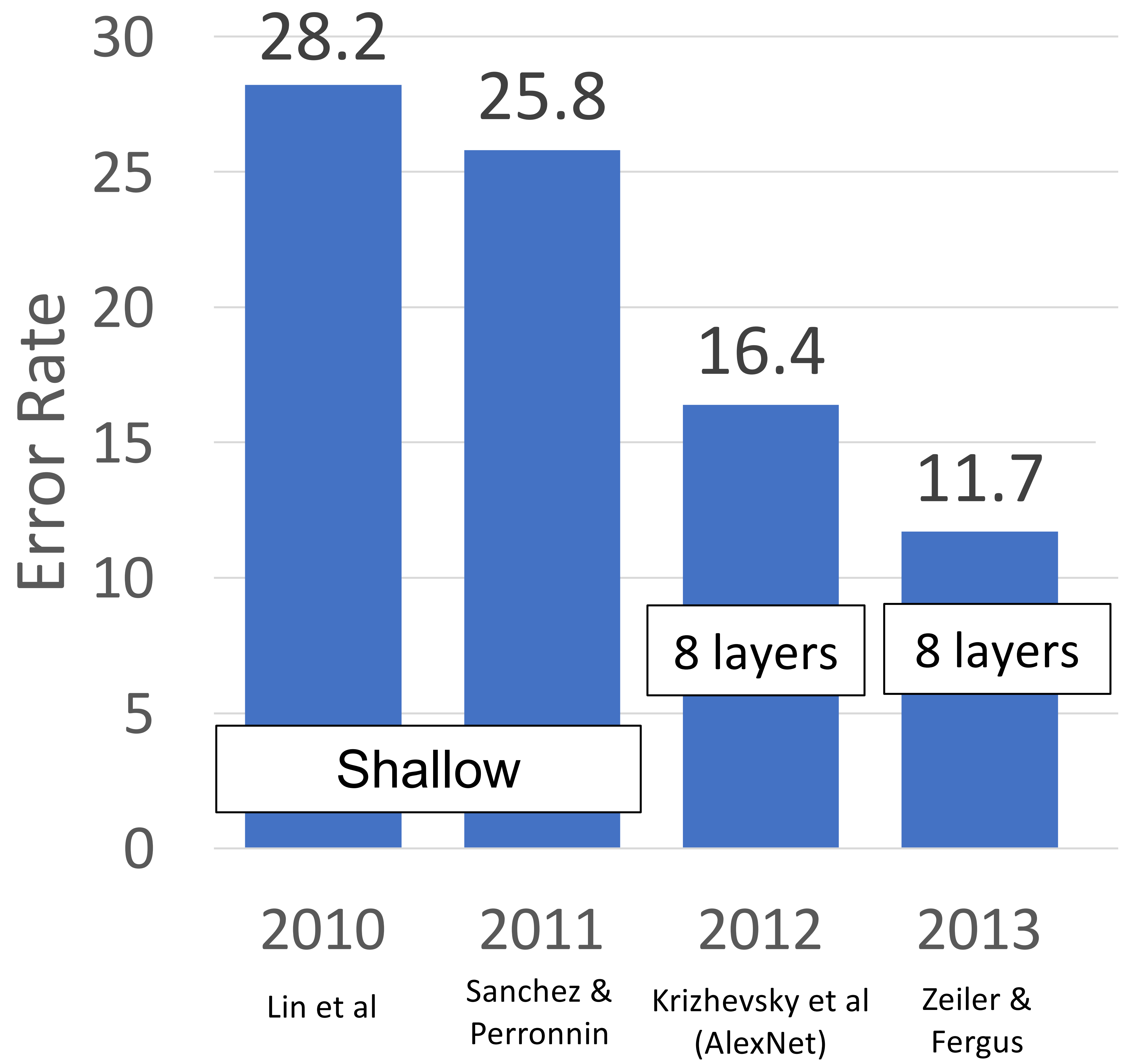
ImageNet top 5 error: 16.4% -> 11.7%



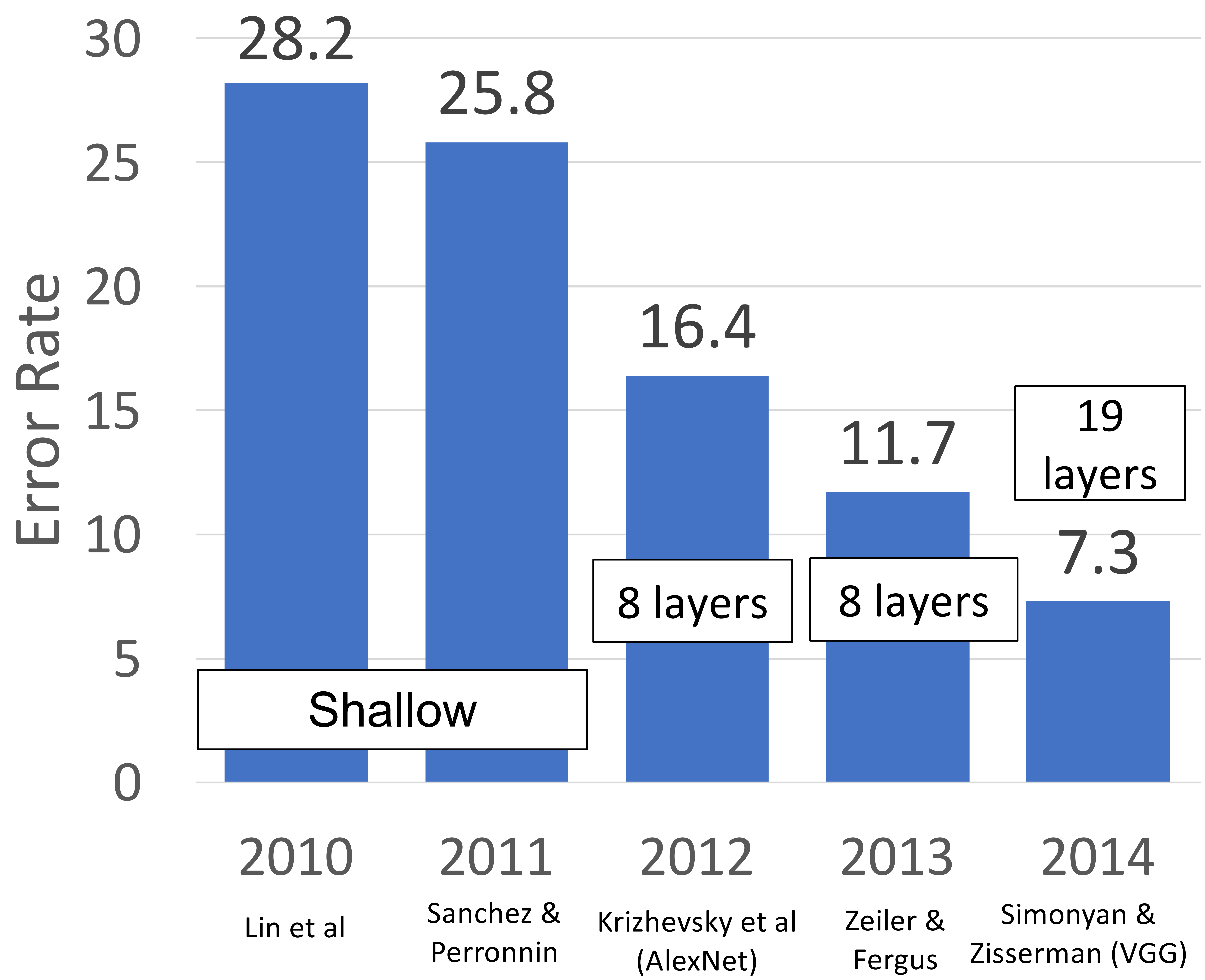
AlexNet but:
Conv1: change from (11x11 stride 4) to (7x7 stride 2)
Conv3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512
More trial and error :(

Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014

ImageNet Classification Challenge



ImageNet Classification Challenge



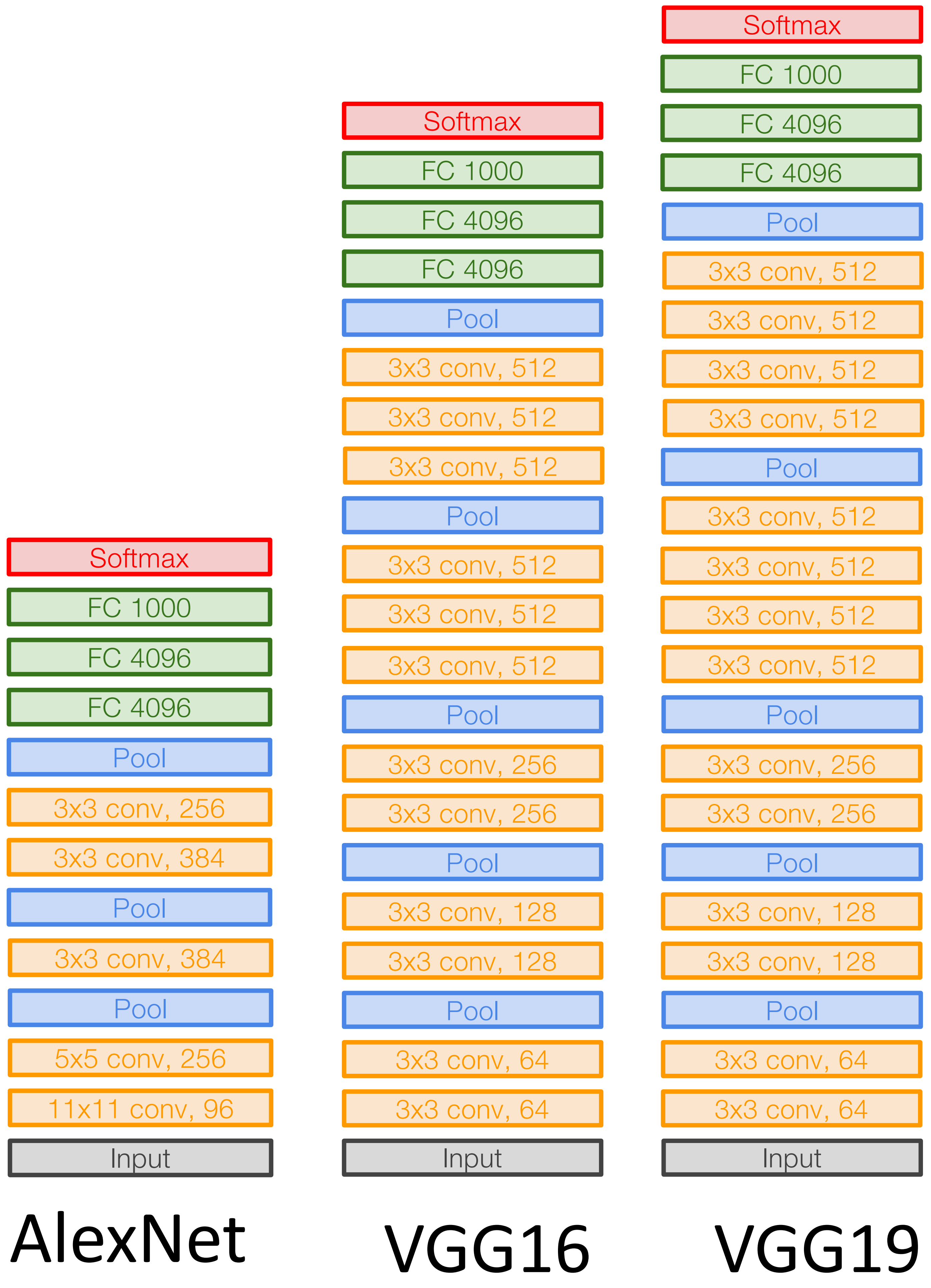
VGG: Deeper Networks, Regular Design

VGG Design rules:

All conv are 3x3 stride 1 pad 1

All max pool are 2x2 stride 2

After pool, double #channels



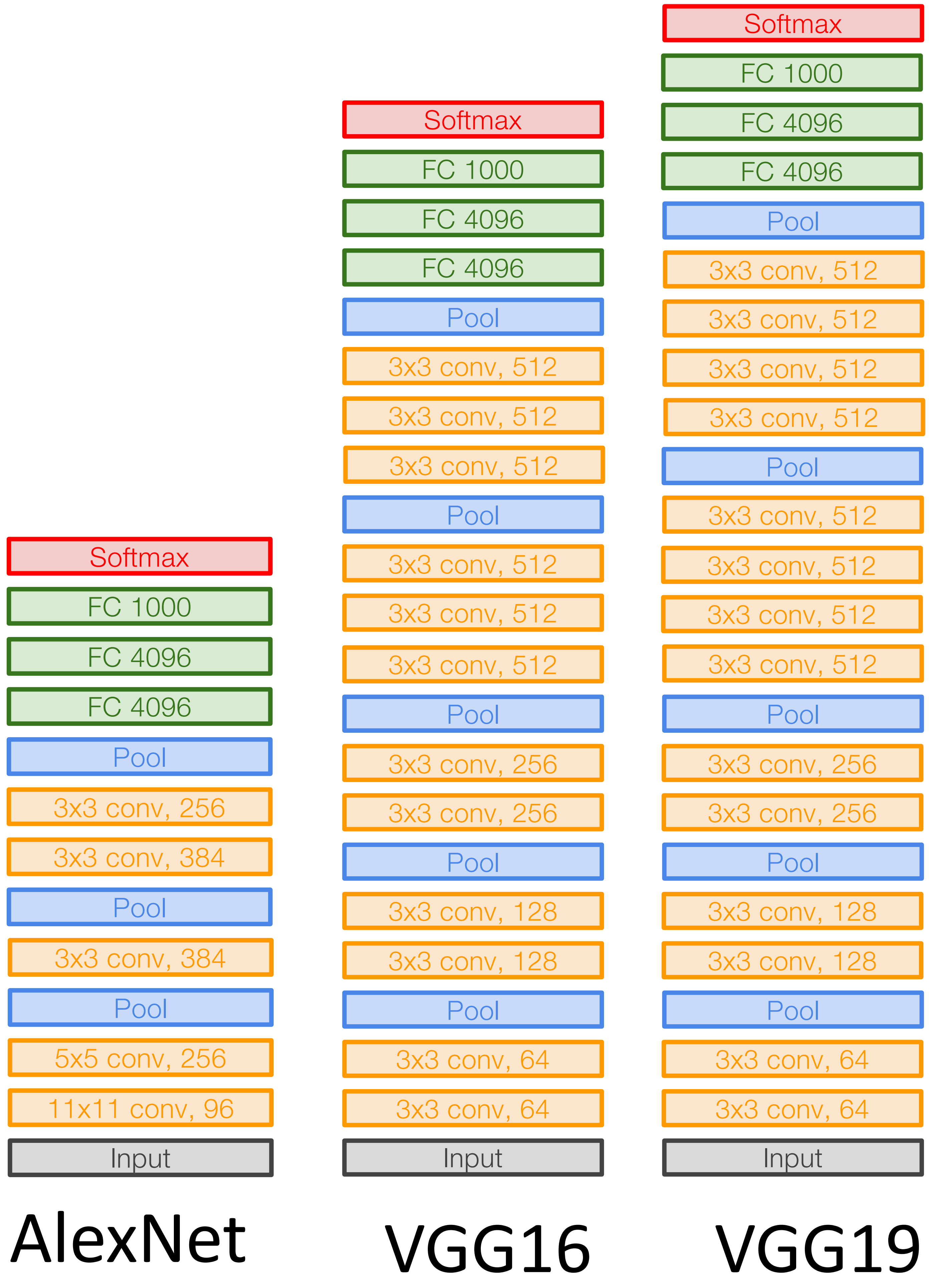
Simonyan and Zissermann, “Very Deep Convolutional Networks for Large-Scale Image Recognition”, ICLR 2015

VGG: Deeper Networks, Regular Design

<u>VGG Design rules:</u>

All conv are 3x3 stride 1 pad 1
All max pool are 2x2 stride 2
After pool, double #channels

Network has 5 convolution **stages**:
Stage 1: conv-conv-pool
Stage 2: conv-conv-pool
Stage 3: conv-conv-pool
Stage 4: conv-conv-conv-[conv]-pool
Stage 5: conv-conv-conv-[conv]-pool



Simonyan and Zissermann, "Very Deep Convolutional Networks for Large-Scale Image Recognition", ICLR 2015

VGG: Deeper Networks, Regular Design

VGG Design rules:

All conv are 3x3 stride 1 pad 1

All max pool are 2x2 stride 2

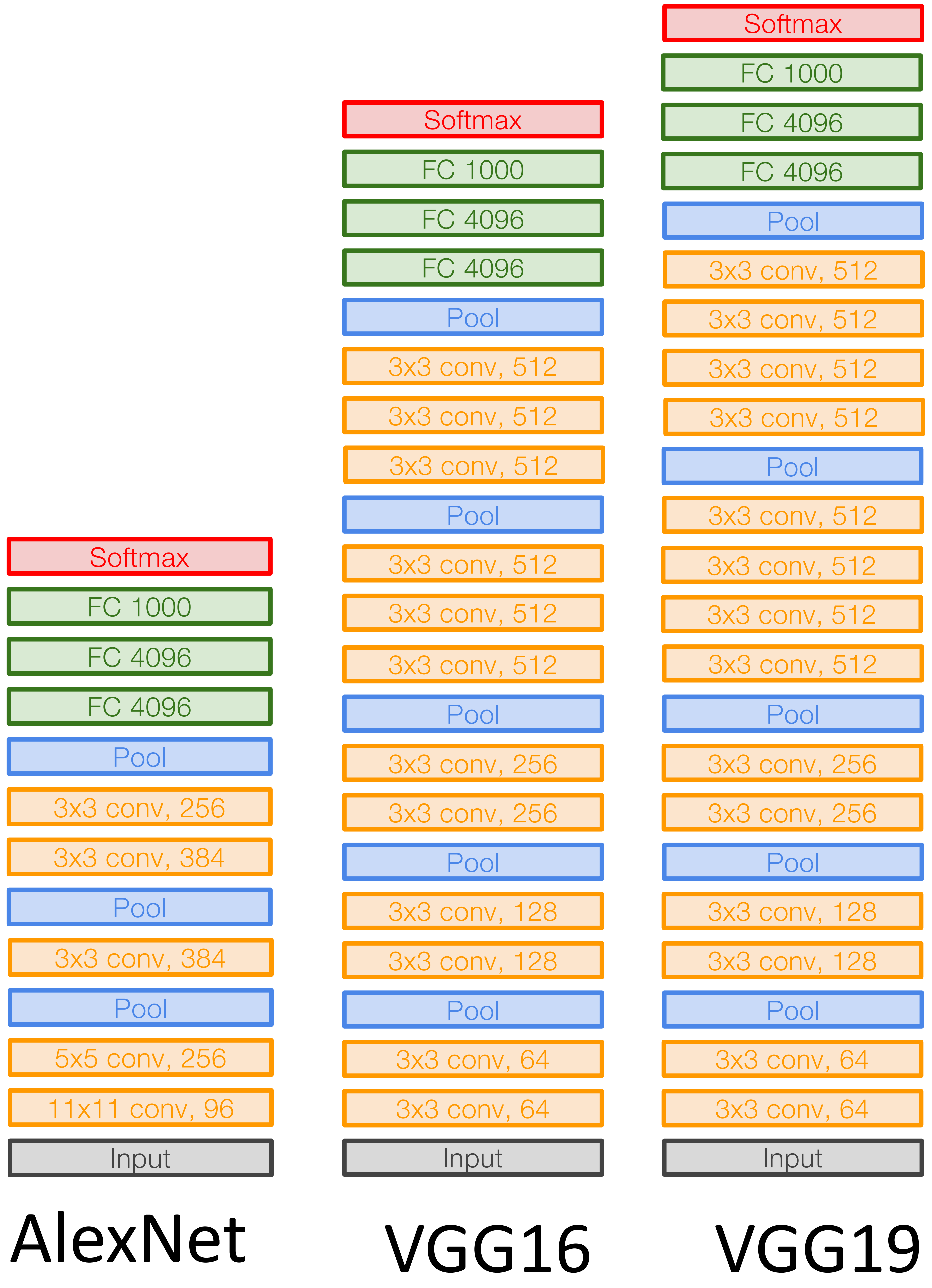
After pool, double #channels

Option 1:

Conv(5x5, C->C)

Params: $25C^2$

FLOPs: $25C^2HW$



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VGG: Deeper Networks, Regular Design

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All conv are 3x3 stride 1 pad 1

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After pool, double #channels

Option 1:

Conv(5x5, C->C)

Params: $25C^2$

FLOPs: $25C^2HW$

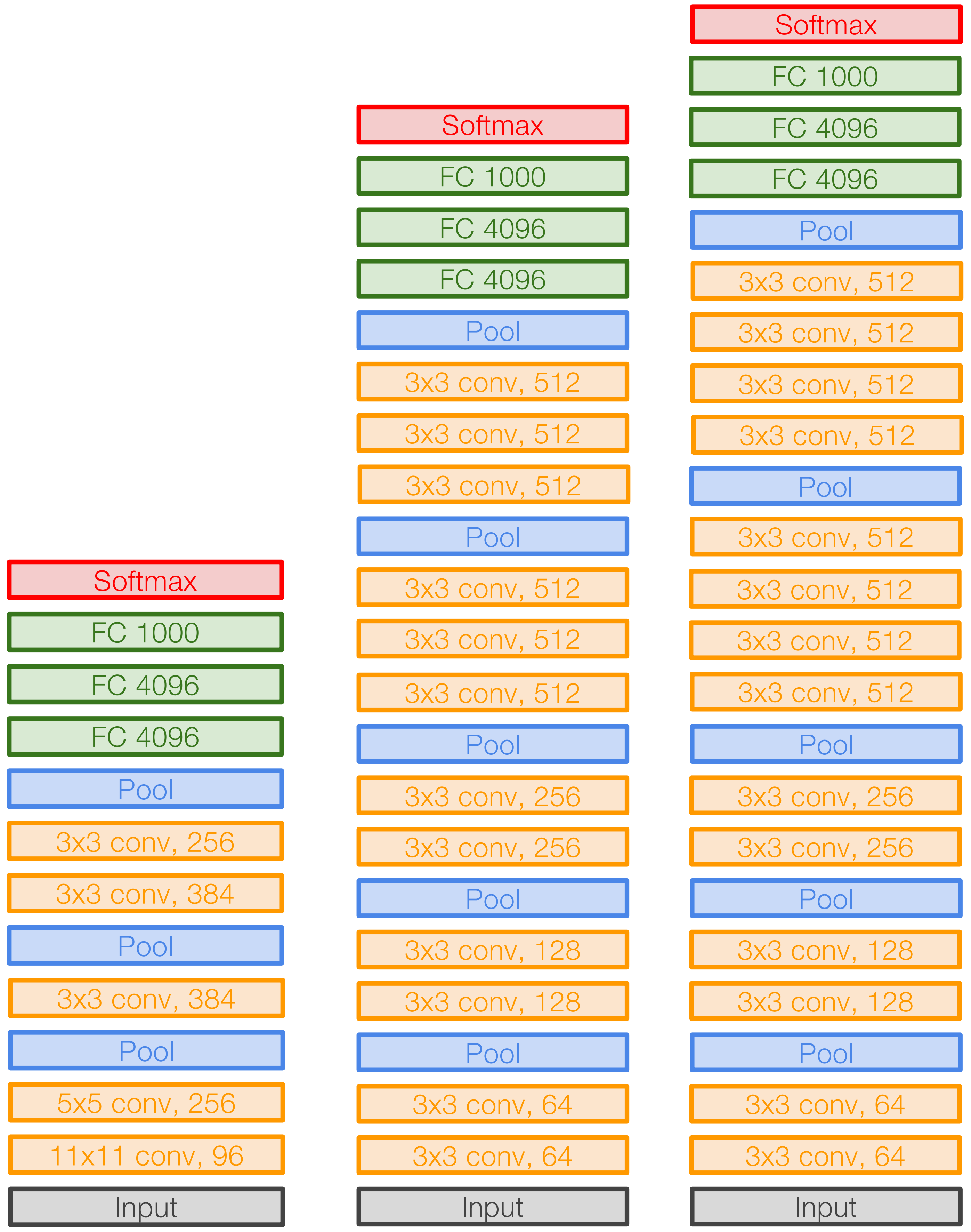
Option 2:

Conv(3x3, C->C)

Conv(3x3, C->C)

Params: $18C^2$

FLOPs: $18C^2HW$



AlexNet VGG16 VGG19

VGG: Deeper Networks, Regular Design

VGG Design rules:

All conv are 3x3 stride 1 pad 1

All max pool are 2x2 stride 2

After pool, double #channels

Two 3x3 conv has same receptive field as a single 5x5 conv, but has fewer parameters and takes less computation!

Option 1:

Conv(5x5, C->C)

Params: $25C^2$

FLOPs: $25C^2HW$

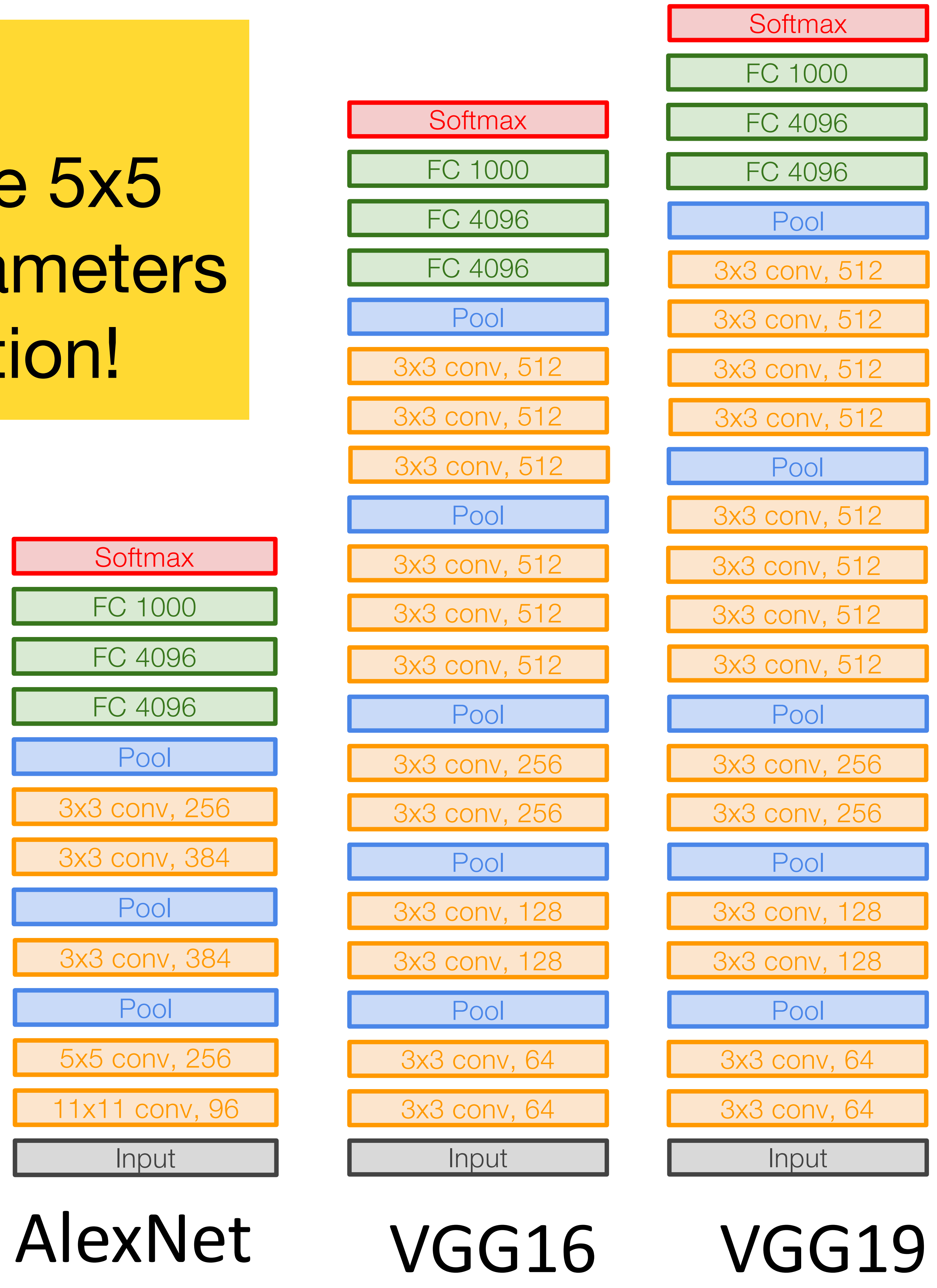
Option 2:

Conv(3x3, C->C)

Conv(3x3, C->C)

Params: $18C^2$

FLOPs: $18C^2HW$



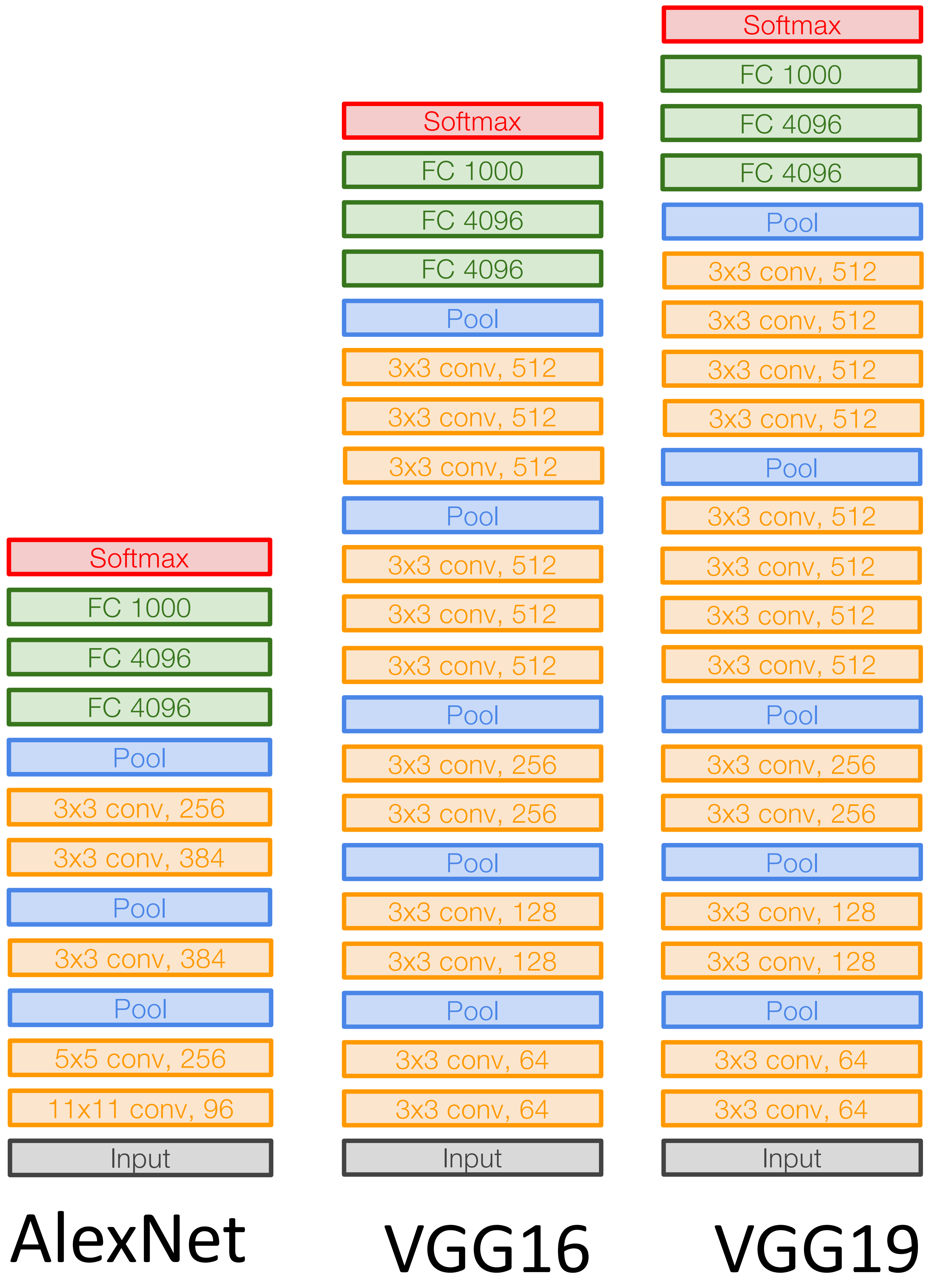
Simonyan and Zissermann, "Very Deep Convolutional Networks for Large-Scale Image Recognition", ICLR 2015

VGG: Deeper Networks, Regular Design

VGG Design rules:
All conv are 3x3 stride 1 pad 1
All max pool are 2x2 stride 2
After pool, double #channels

Option 1:
Input: C x 2H x 2W
Layer: Conv(3x3, C->C)

Memory: 4HWC
Params: $9C^2$
FLOPs: $36HWC^2$



VGG: Deeper Networks, Regular Design

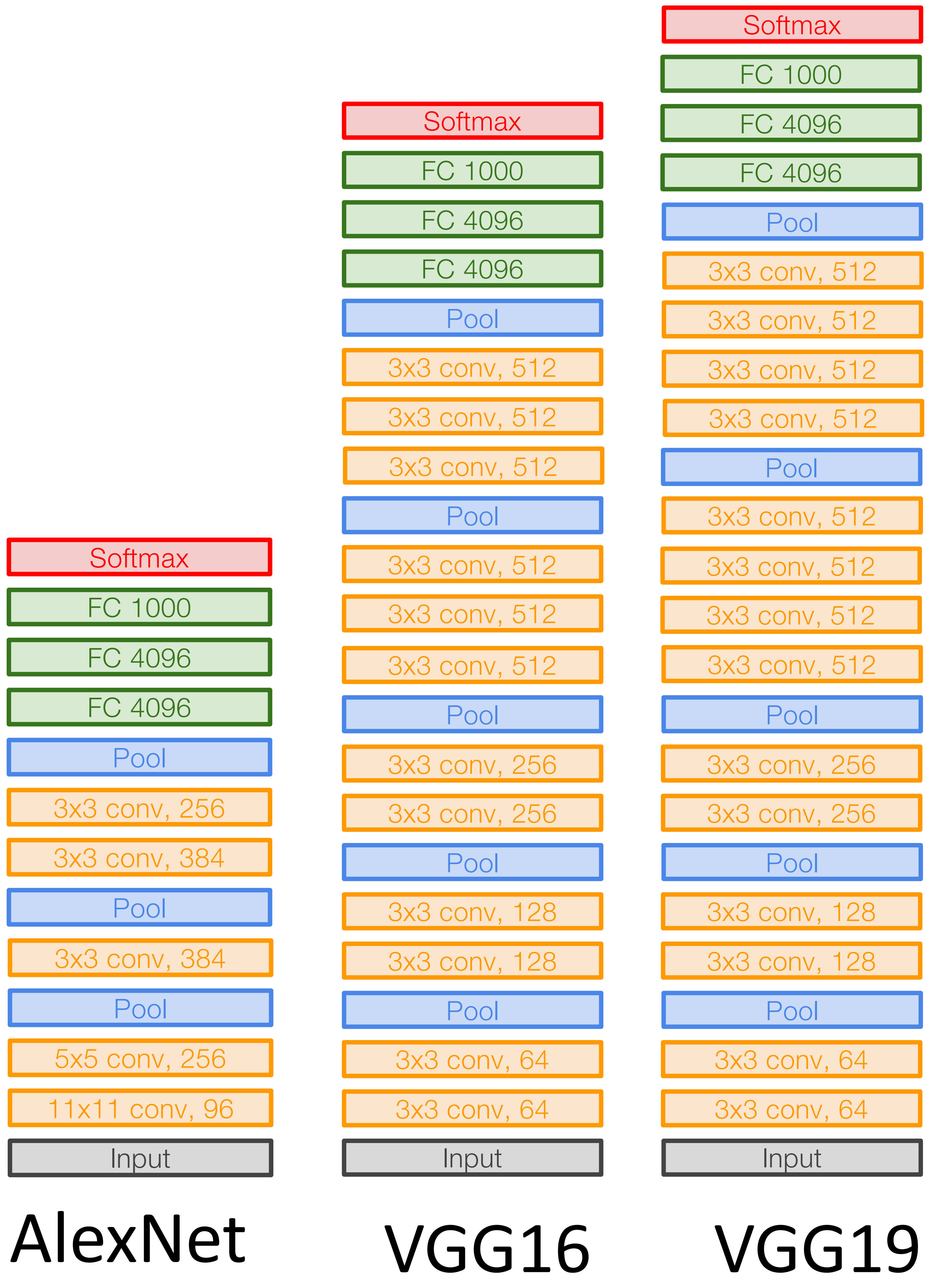
<u>VGG Design rules:</u>
All conv are 3x3 stride 1 pad 1
All max pool are 2x2 stride 2
After pool, double #channels

<u>Option 1:</u>
<u>Input:</u> C x 2H x 2W
<u>Layer:</u> Conv(3x3, C->C)

Memory: 4HWC
Params: $9C^2$
FLOPs: $36HWC^2$

<u>Option 2:</u>
<u>Input:</u> 2C x H x W
<u>Layer:</u> Conv(3x3, 2C->2C)

Memory: 2HWC
Params: $36C^2$
FLOPs: $36HWC^2$



Simonyan and Zissermann, “Very Deep Convolutional Networks for Large-Scale Image Recognition”, ICLR 2015

VGG: Deeper Networks, Regular Design

VGG Design rules:

All conv are 3x3 stride 1 pad 1

All max pool are 2x2 stride 2

After pool, double #channels

Conv layers at each spatial resolution take the same amount of computation!

Option 1:

Input: C x 2H x 2W

Layer: Conv(3x3, C->C)

Memory: 4HWC

Params: $9C^2$

FLOPs: $36HWC^2$

Option 2:

Input: 2C x H x W

Layer: Conv(3x3, 2C->2C)

Memory: 2HWC

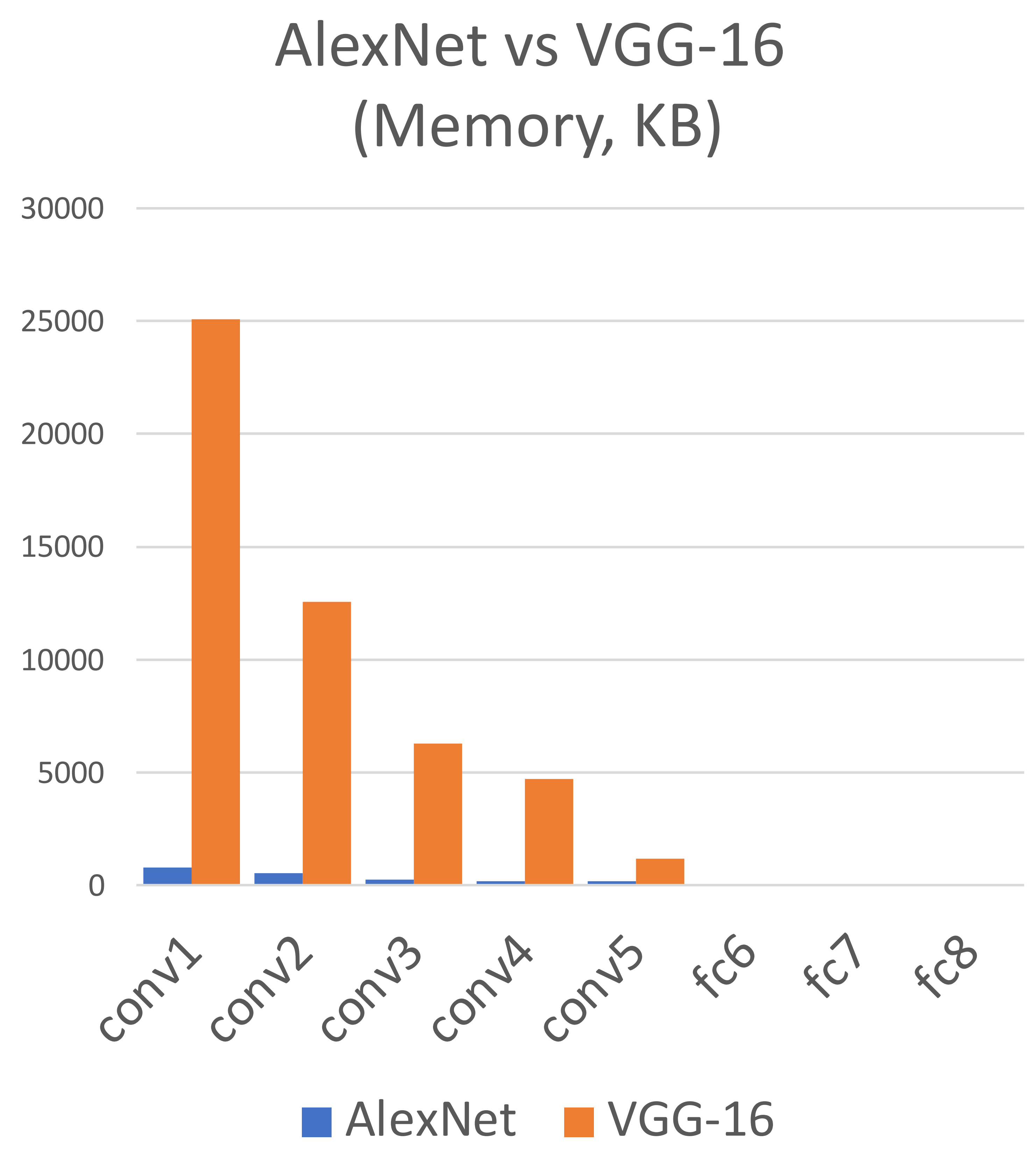
Params: $36C^2$

FLOPs: $36HWC^2$

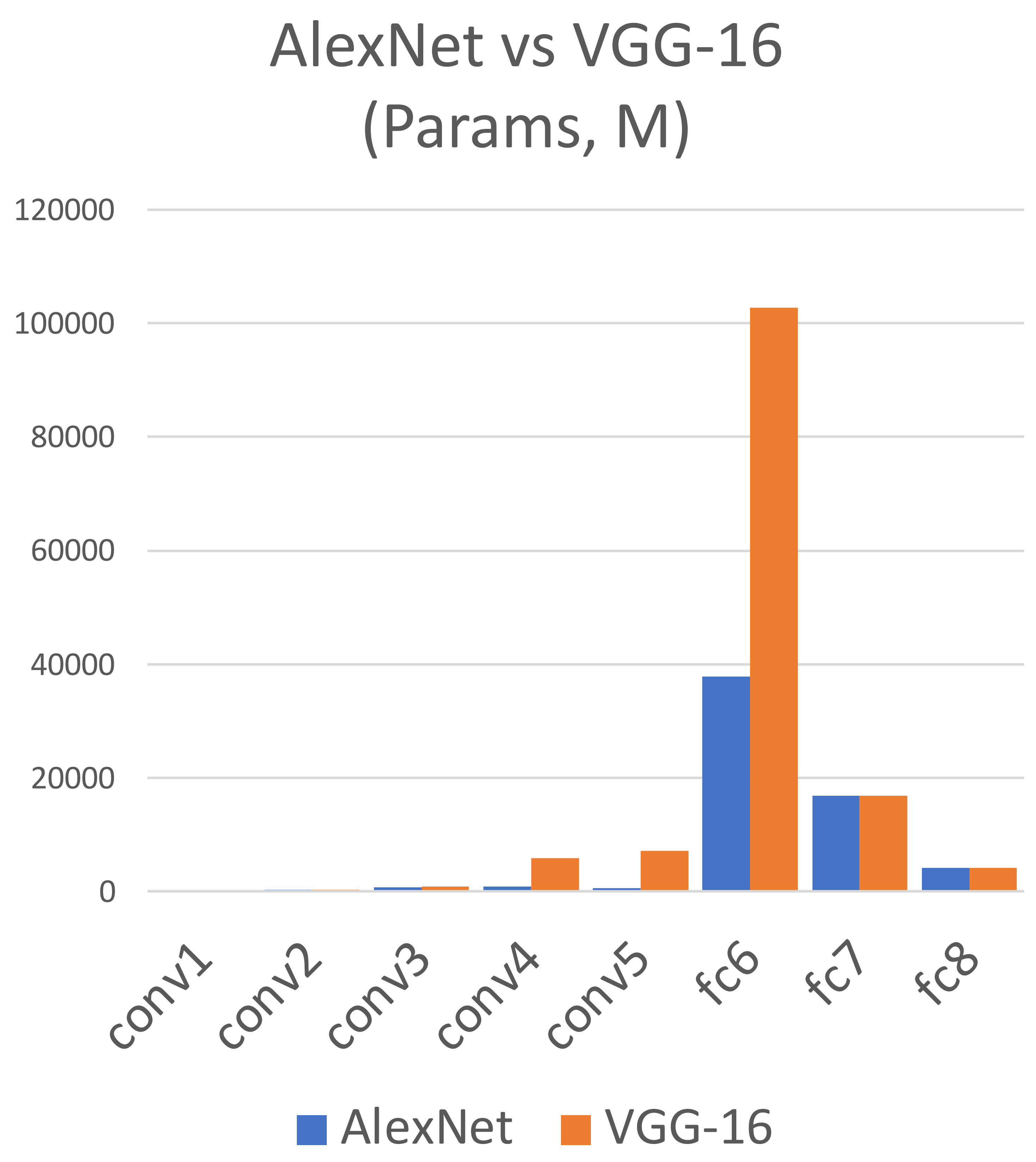
AlexNet VGG16 VGG19

Simonyan and Zissermann, "Very Deep Convolutional Networks for Large-Scale Image Recognition", ICLR 2015

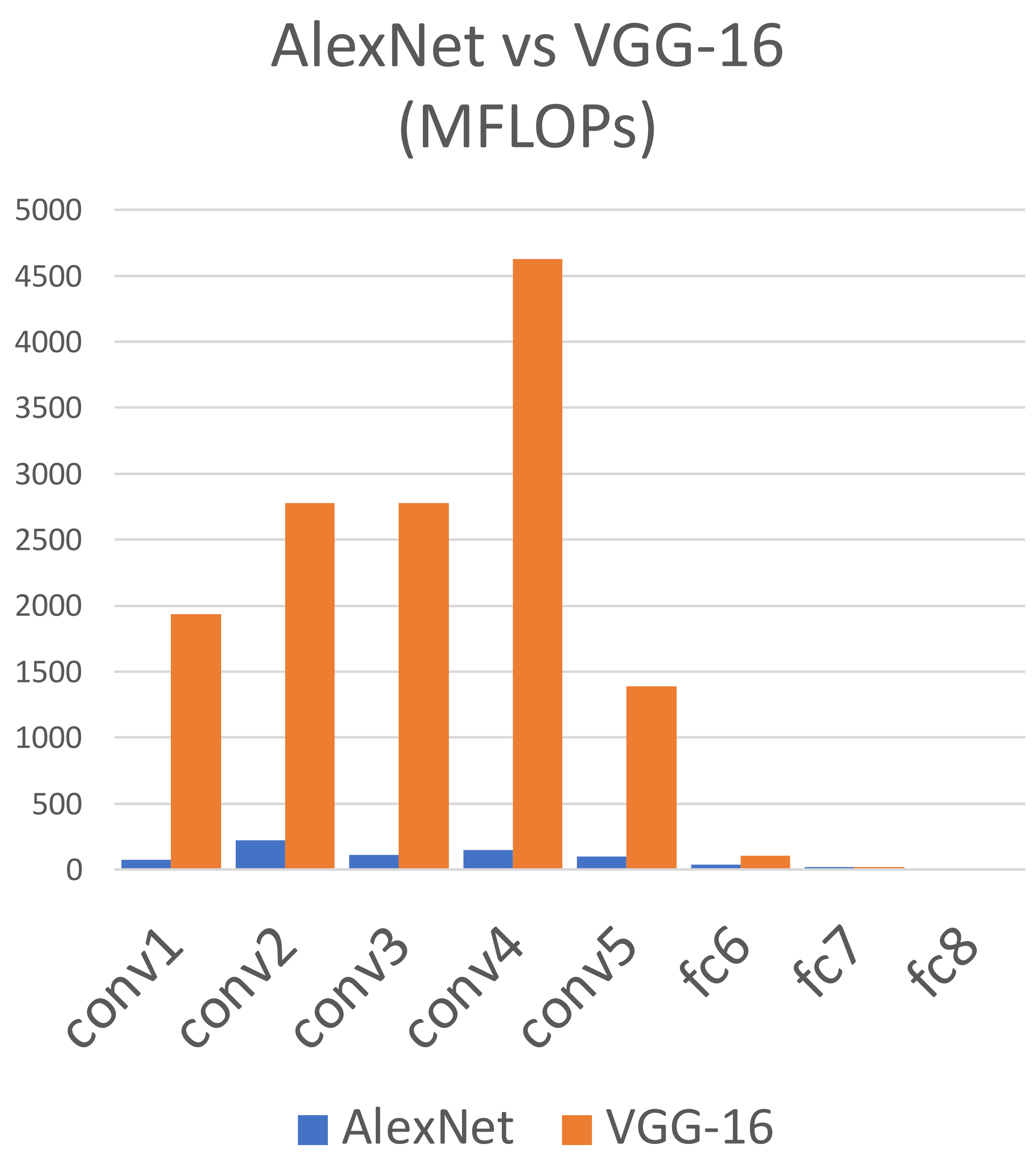
AlexNet vs VGG-16: Much bigger network!



AlexNet total: 1.9MB
VGG-16 total: 48.6MB (25x)

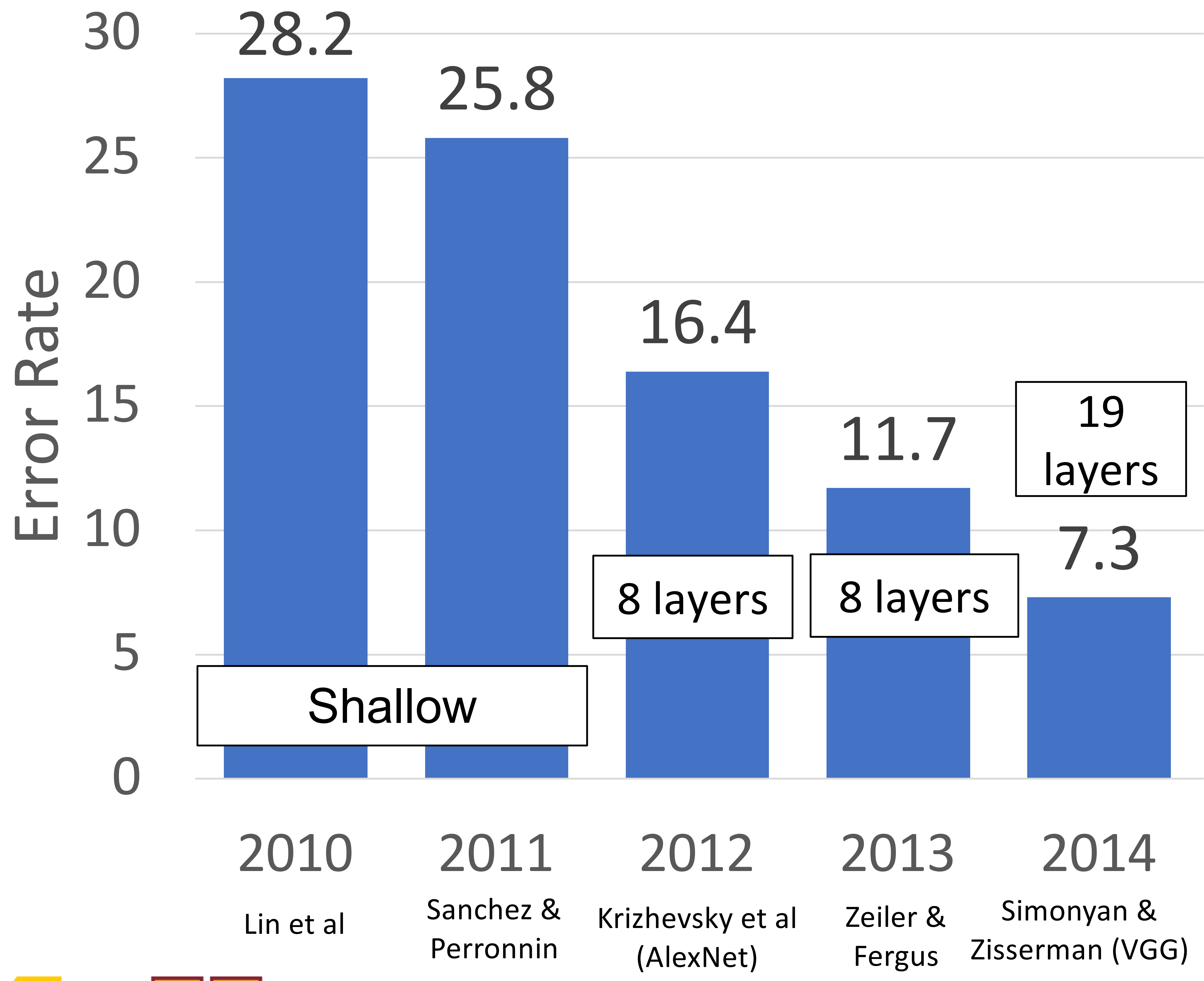


AlexNet total: 61M
VGG-16 total: 138M (2.3x)

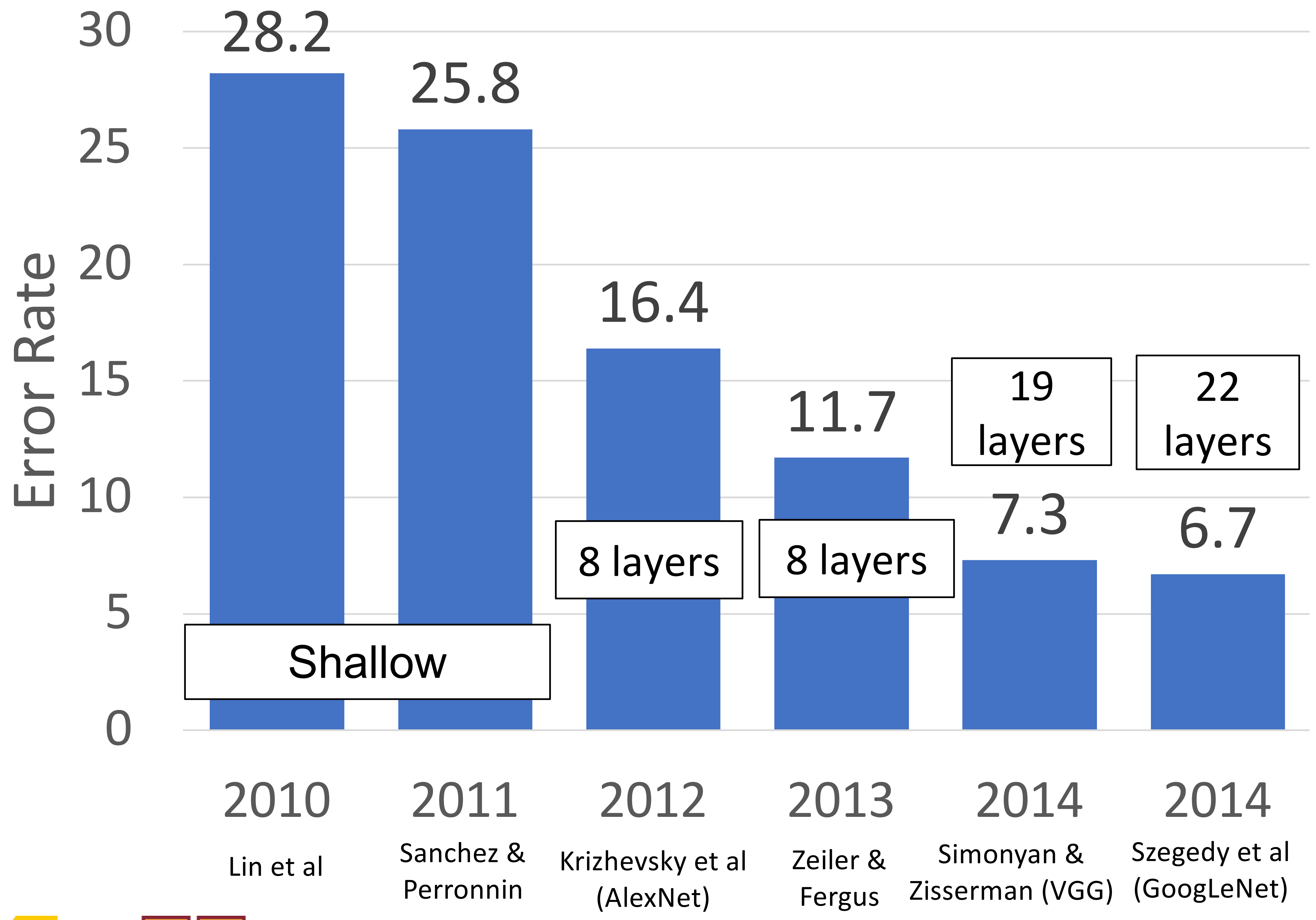


AlexNet total: 0.7 GFLOP
VGG-16 total: 13.6 GFLOP (19.4x)

ImageNet Classification Challenge

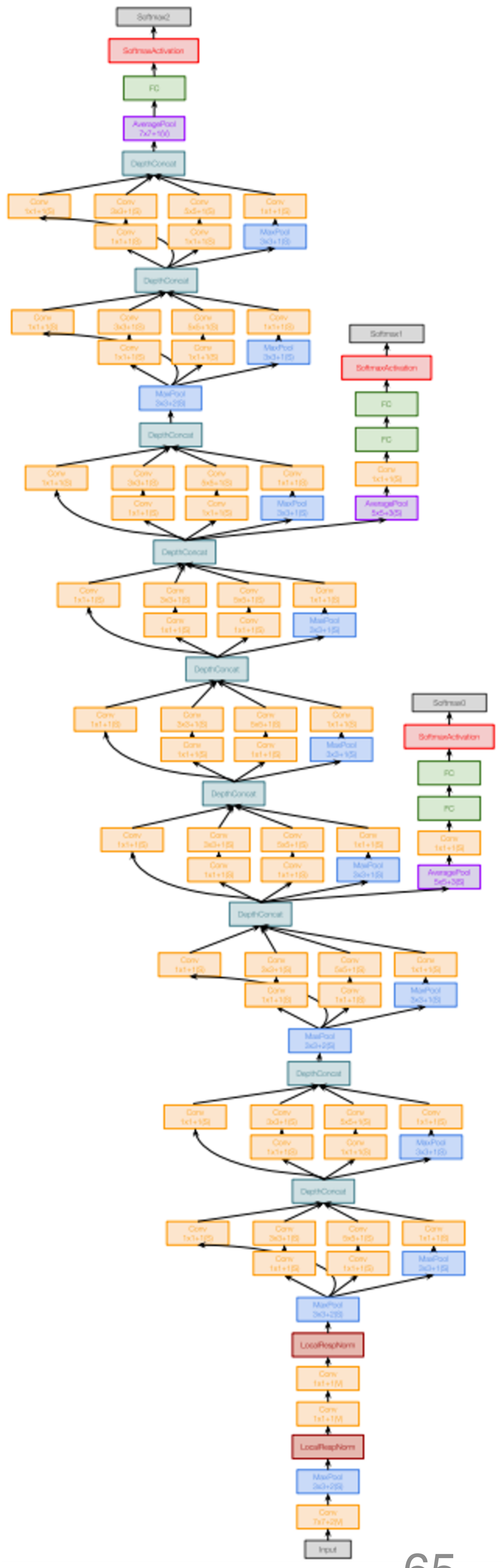


ImageNet Classification Challenge



GoogLeNet: Focus on Efficiency

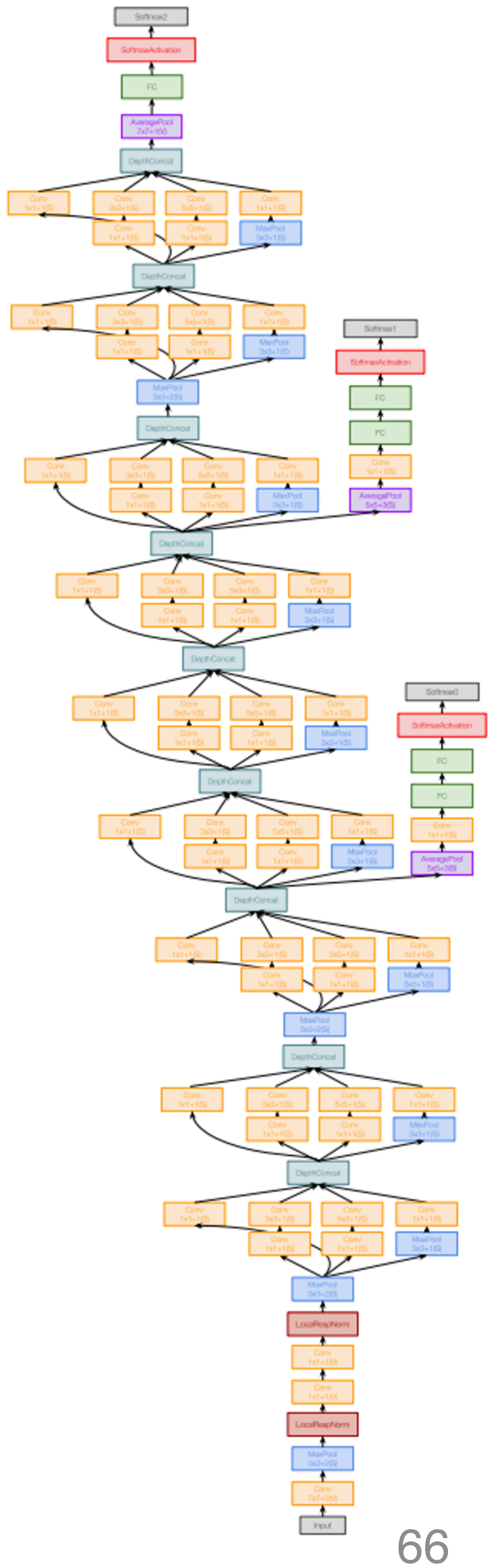
Many innovations for efficiency: reduce parameter count, memory usage, and computation



Szegedy et al, “Going deeper with convolutions”, CVPR 2015

GoogLeNet: Aggressive Stem

Stem network at the start aggressively downsamples input
(Recall in VGG-16: Most of the compute was at the start)

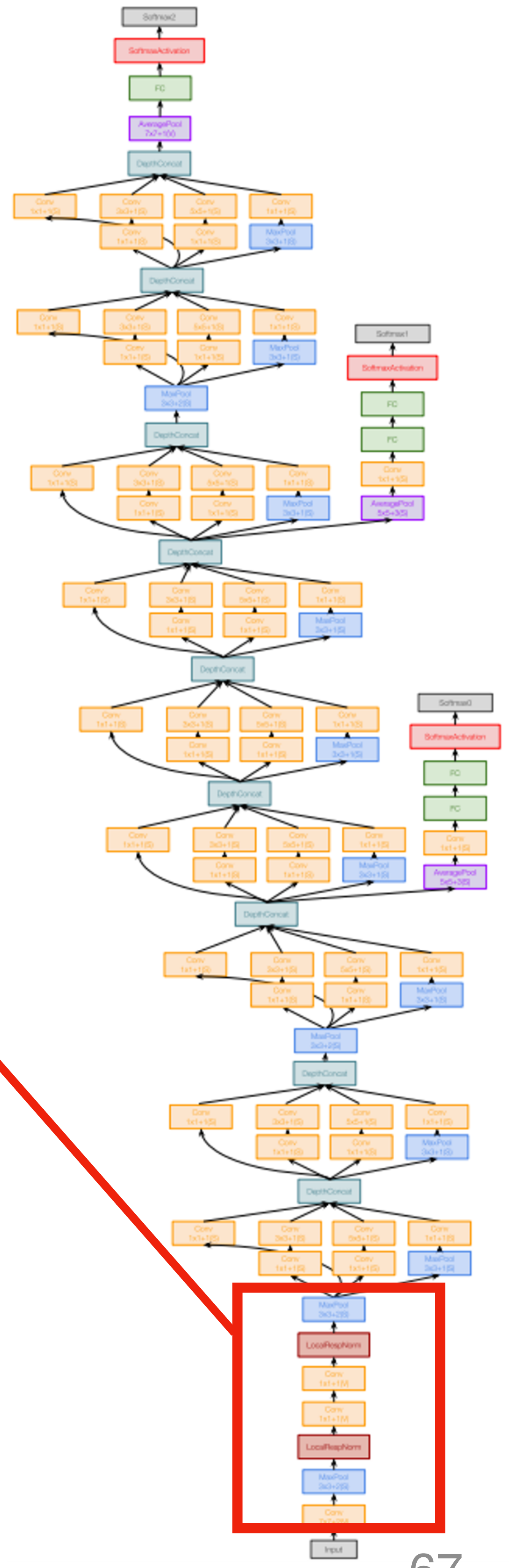


Szegedy et al, "Going deeper with convolutions", CVPR 2015

GoogLeNet: Aggressive Stem

Stem network at the start aggressively downsamples input
(Recall in VGG-16: Most of the compute was at the start)

	Input size		**Layer**				**Output size**				
Layer	C	H/W	Filters	Kernel	Strid	Pad	C	H/W	Memory	Params	Flop (M)
Conv	3	224	64	7	2	3	64	112	3316	9	118
Max-pool	64	112		3	2	1	64	56	784	0	2
Conv	64	56	64	1	1	0	64	56	784	4	13
Conv	64	56	192	3	1	1	192	56	2352	111	347
Max-pool	192	56		3	2	1	192	28	588	0	1



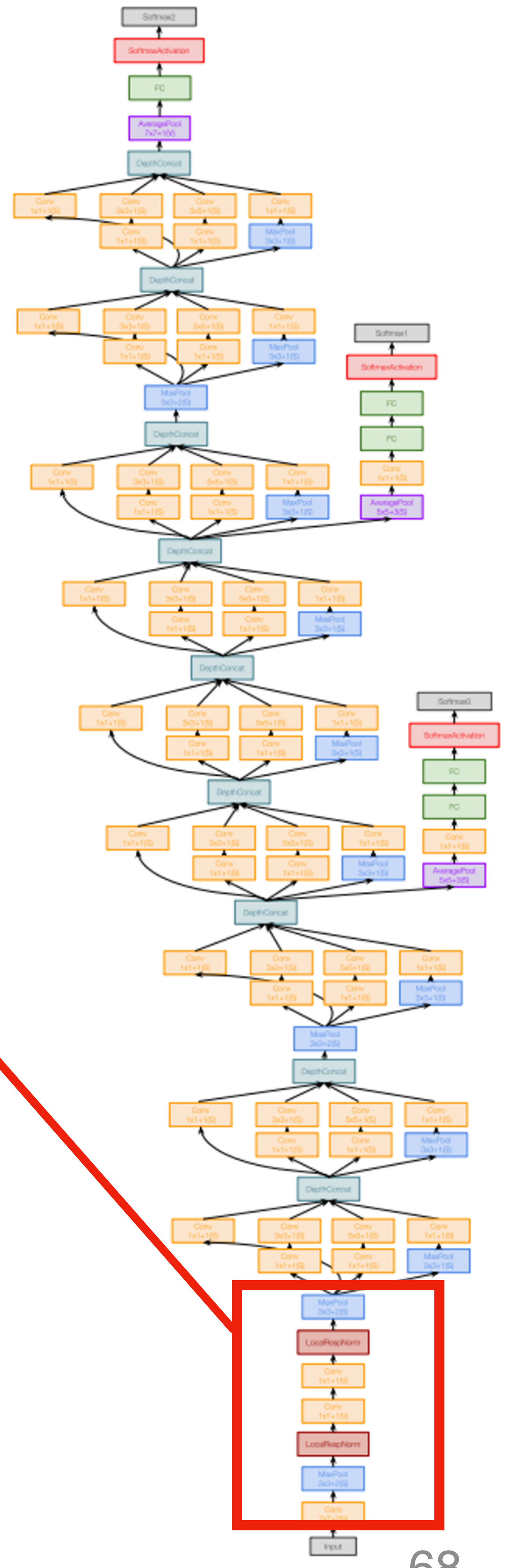
Total from 224 to 28 spatial resolution:
Memory: 7.5 MB
Params: 124K
MFLOP: 418

Szegedy et al, “Going deeper with convolutions”, CVPR 2015

GoogLeNet: Aggressive Stem

Stem network at the start aggressively downsamples input
(Recall in VGG-16: Most of the compute was at the start)

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Strid	Pad	C	H/W	Memory	Params	Flop (M)
Conv	3	224	64	7	2	3	64	112	3316	9	118
Max-pool	64	112		3	2	1	64	56	784	0	2
Conv	64	56	64	1	1	0	64	56	784	4	13
Conv	64	56	192	3	1	1	192	56	2352	111	347
Max-pool	192	56		3	2	1	192	28	588	0	1



<u>Total from 224 to 28 spatial resolution:</u>
Memory: 7.5 MB
Params: 124K
MFLOP: 418

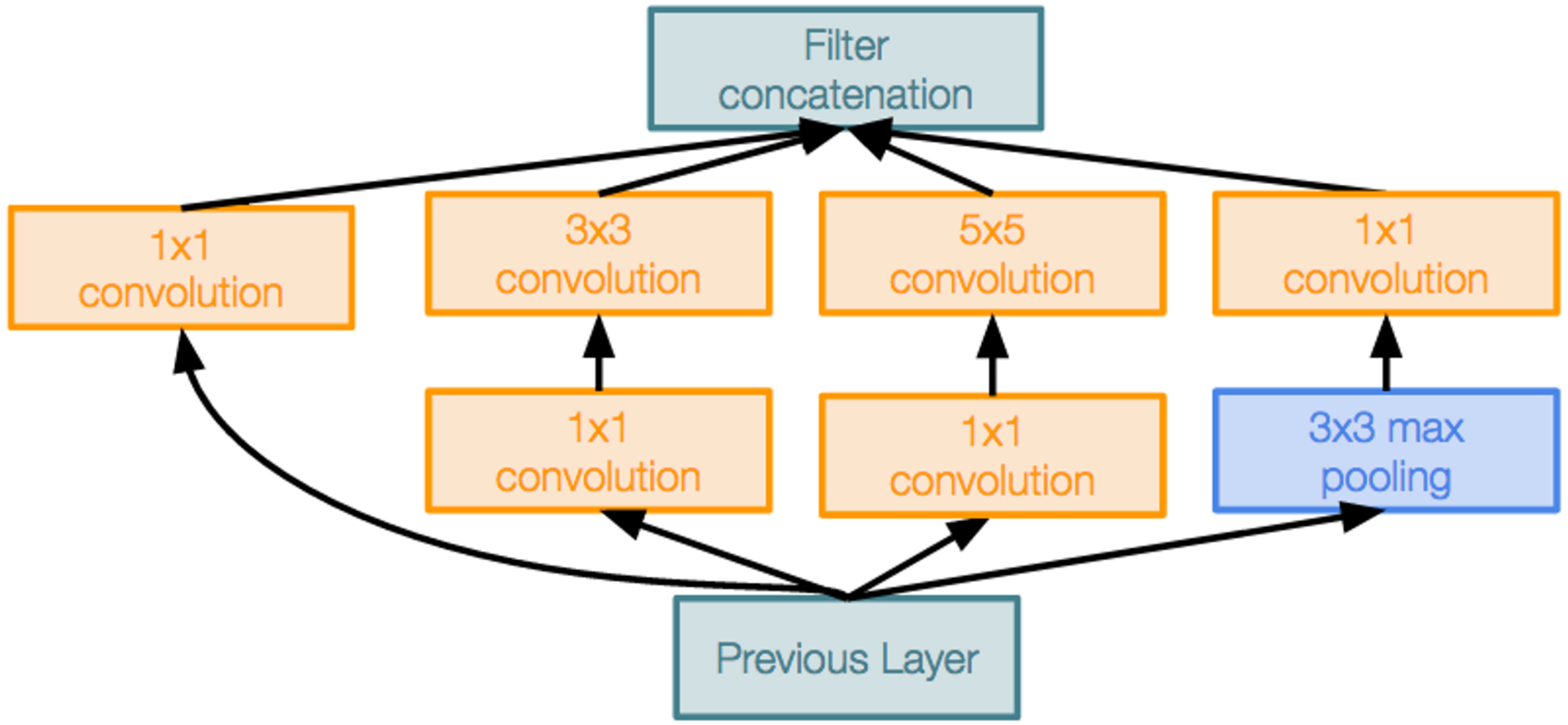
<u>Compare VGG-16:</u>
Memory: 42.9 MB (5.7x)
Params: 1.1M (8.9x)
MFLOP: 7485 (17.8x)

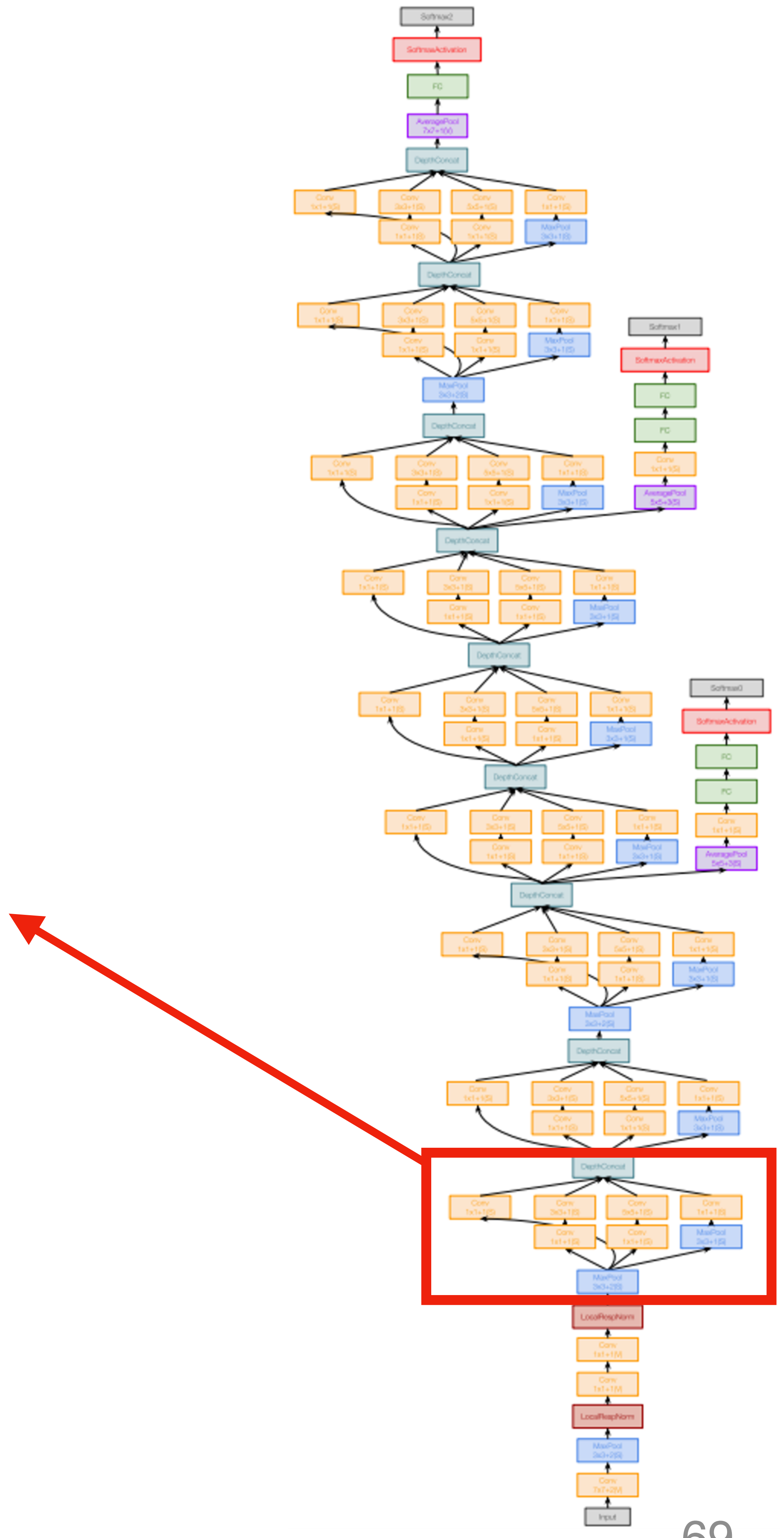
Szegedy et al, “Going deeper with convolutions”, CVPR 2015

GoogLeNet: Inception Module

Inception module: Local unit with parallel branches

Local structure repeated many times throughout the network





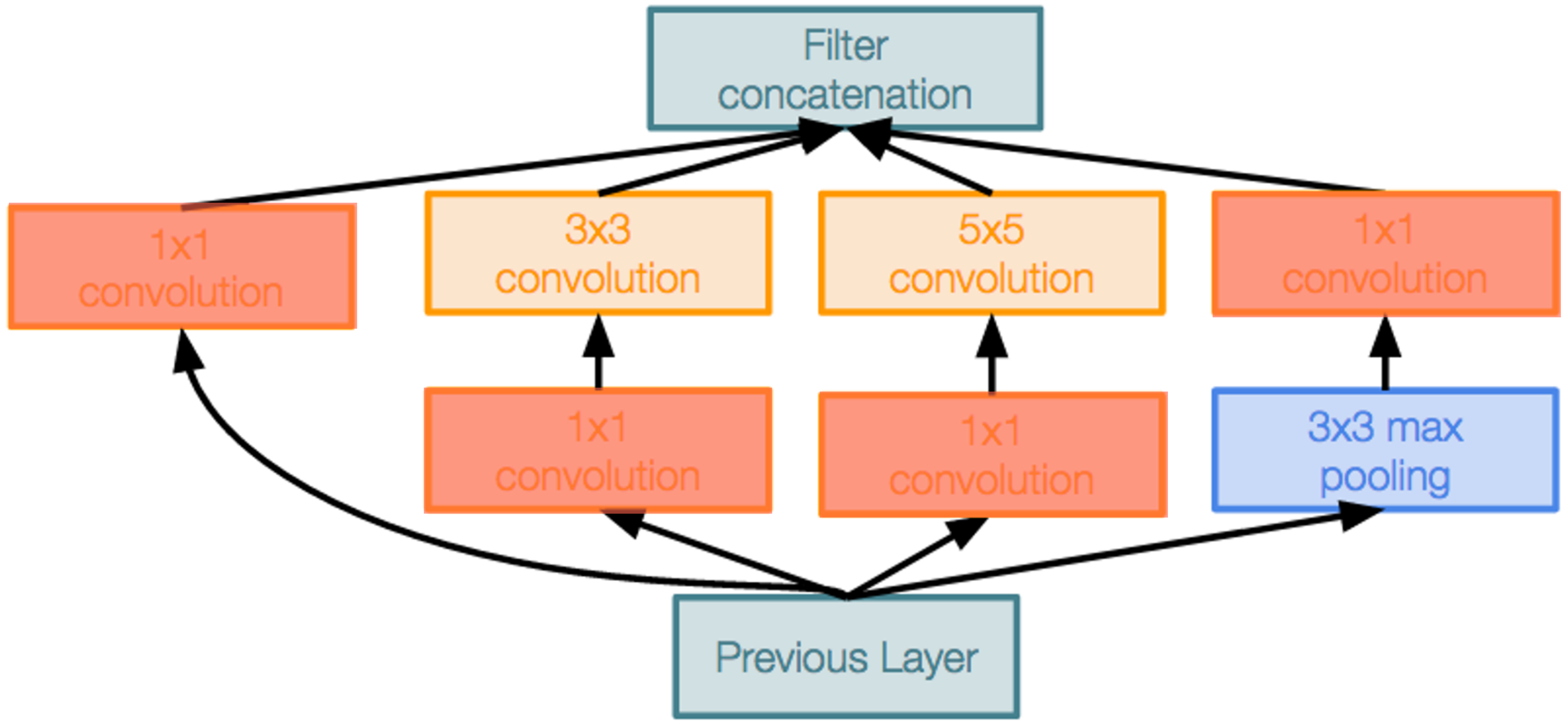
Szegedy et al, “Going deeper with convolutions”, CVPR 2015

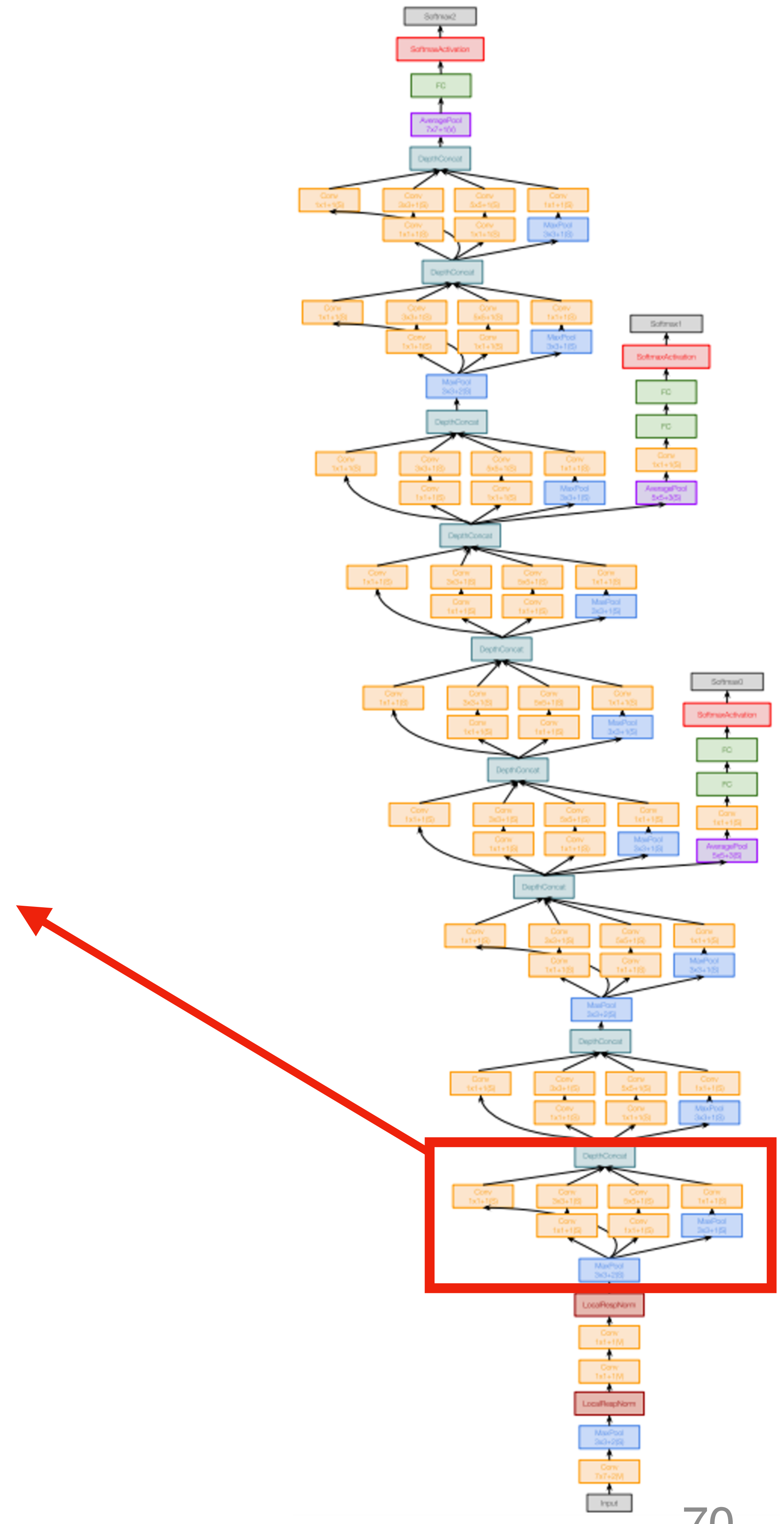
GoogLeNet: Inception Module

Inception module: Local unit with parallel branches

Local structure repeated many times throughout the network

Uses 1x1 "Bottleneck" layers to reduce channel dimension before expensive conv (we will revisit this with ResNet!)





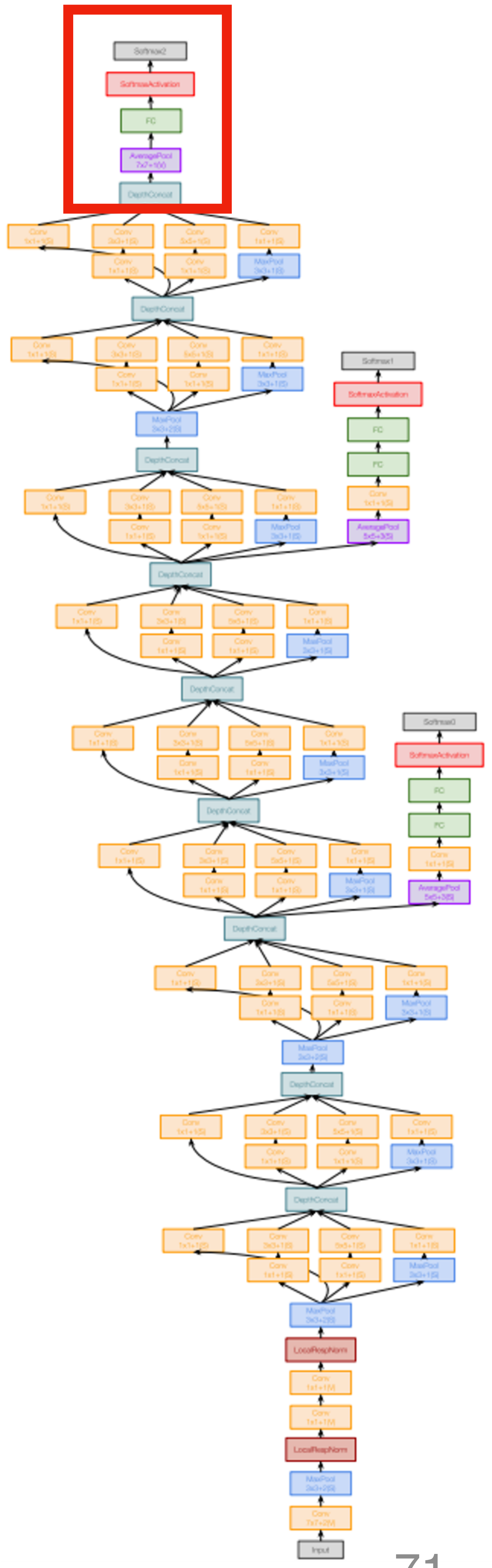
Szegedy et al, "Going deeper with convolutions", CVPR 2015

GoogLeNet: Global Average Pooling

No large FC layers at the end!

Instead use **global average pooling** to collapse spatial dimensions, and one linear layer to produce class scores
(Recall VGG-16: Most parameters were in the FC layers!)

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params	Flop (M)
avg-pool	1024	7		7	1	0	1024	1	4	0	0
fc	1024		1000				1000	0	0	1025	1



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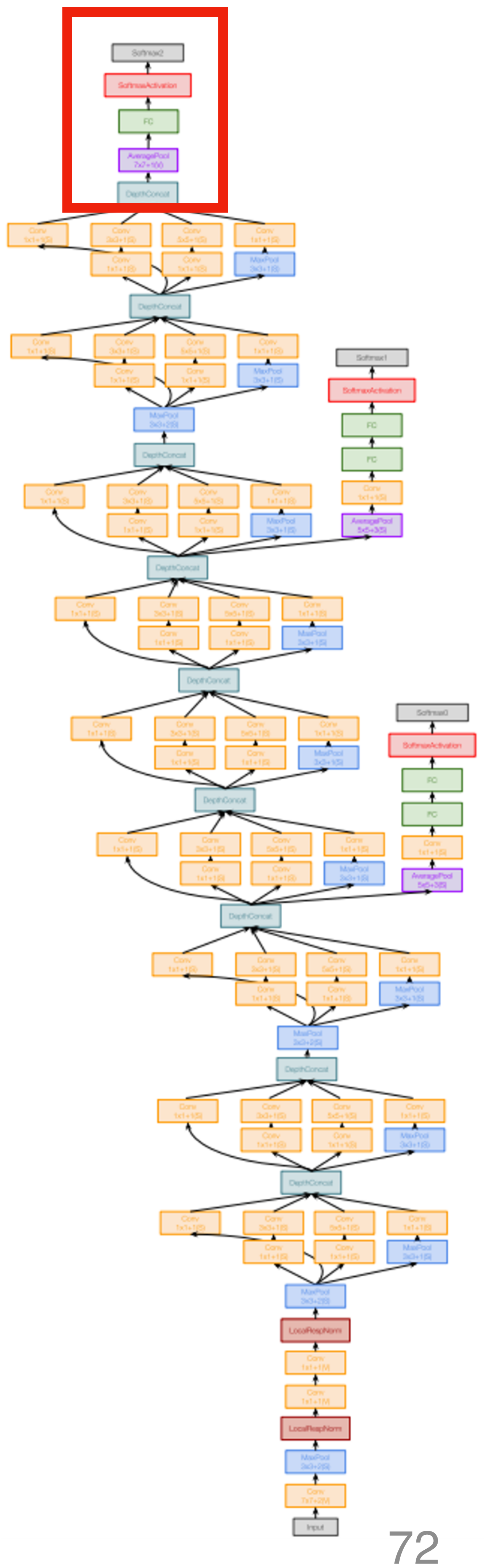
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params	Flop (M)
avg-pool	1024	7		7	1	0	1024	1	4	0	0
fc	1024		1000				1000	0	0	1025	1

Compare with VGG-16:

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params	Flop (M)
Flatten	512	7					25088		98		
FC6	25088			4096			4096		16	102760	103
FC7	4096			4096			4096		16	16777	17
FC8	4096			1000			1000		4	4096	4

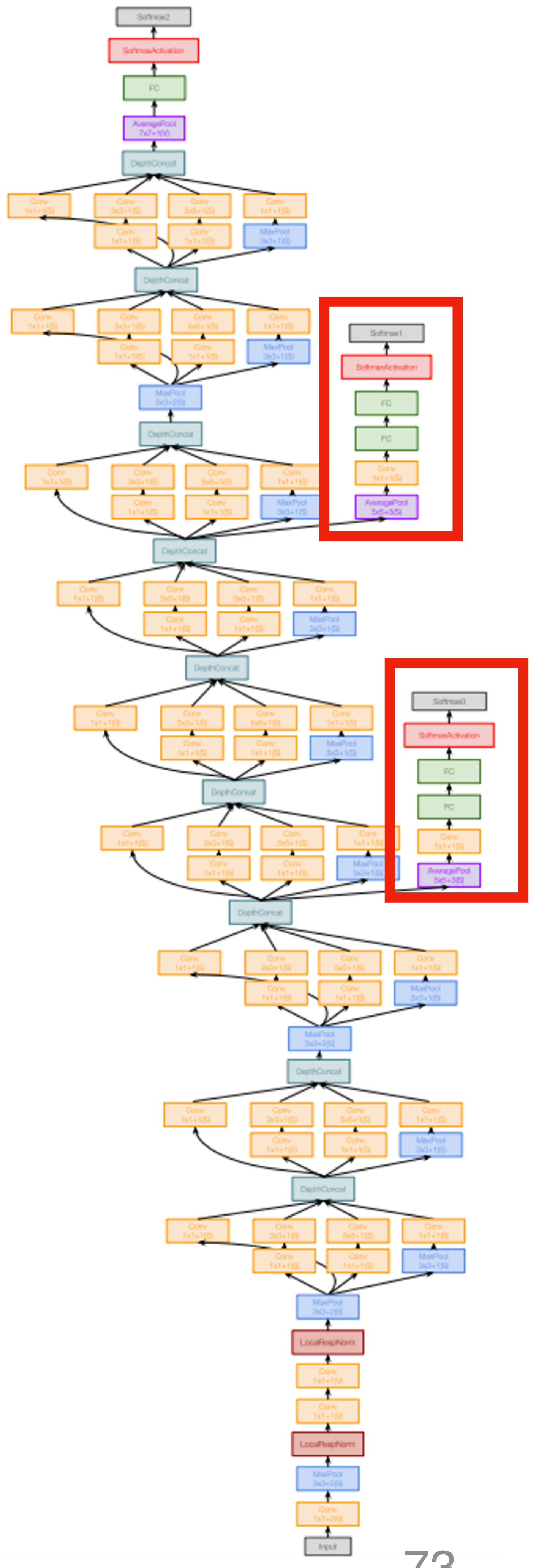


GoogLeNet: Auxiliary Classifiers

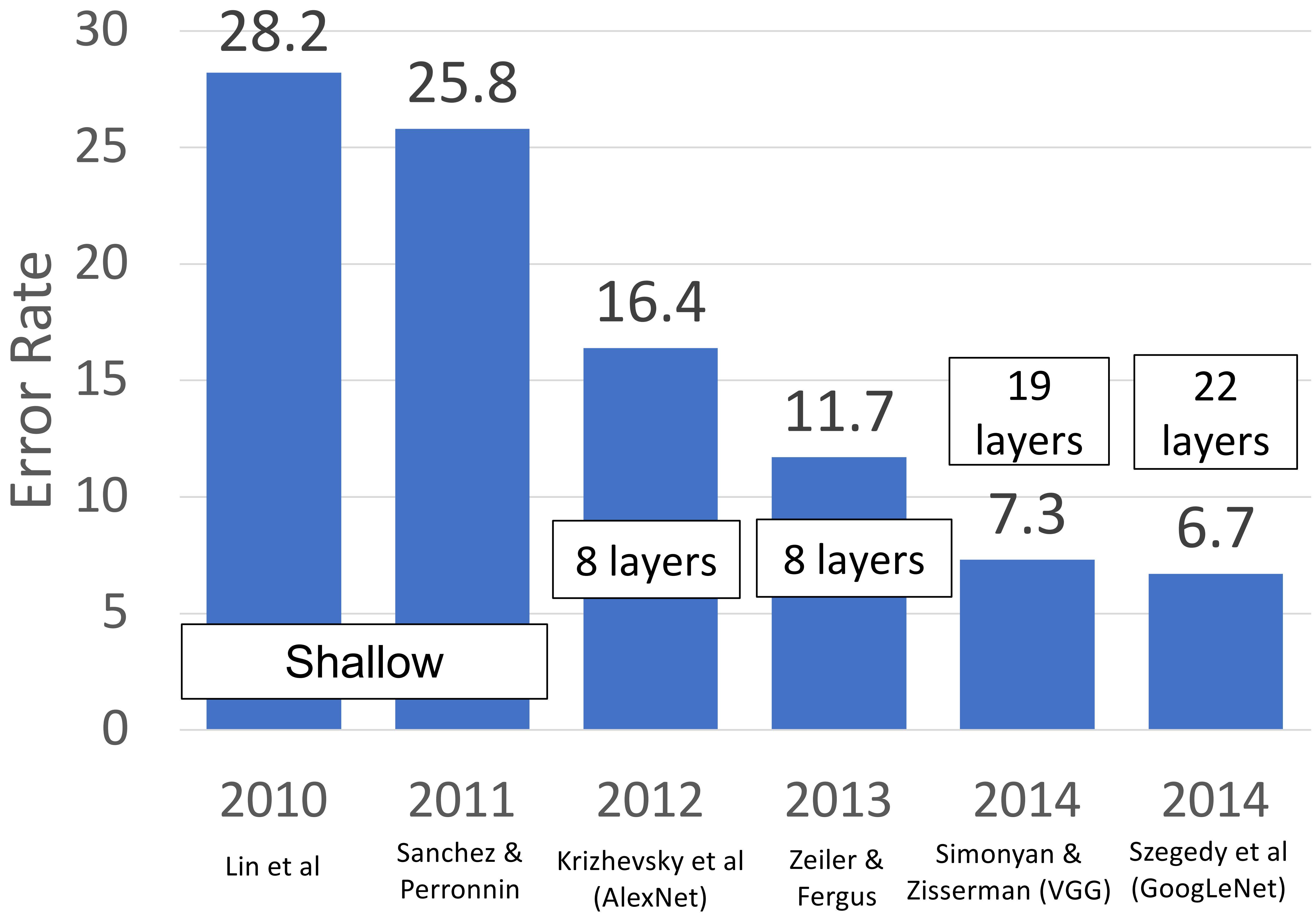
Training using loss at the end of the network didn't work well: Network is too deep, gradients don't propagate cleanly

As a hack, attach "auxiliary classifiers" at several intermediate points in the network that also try to classify the image and receive loss

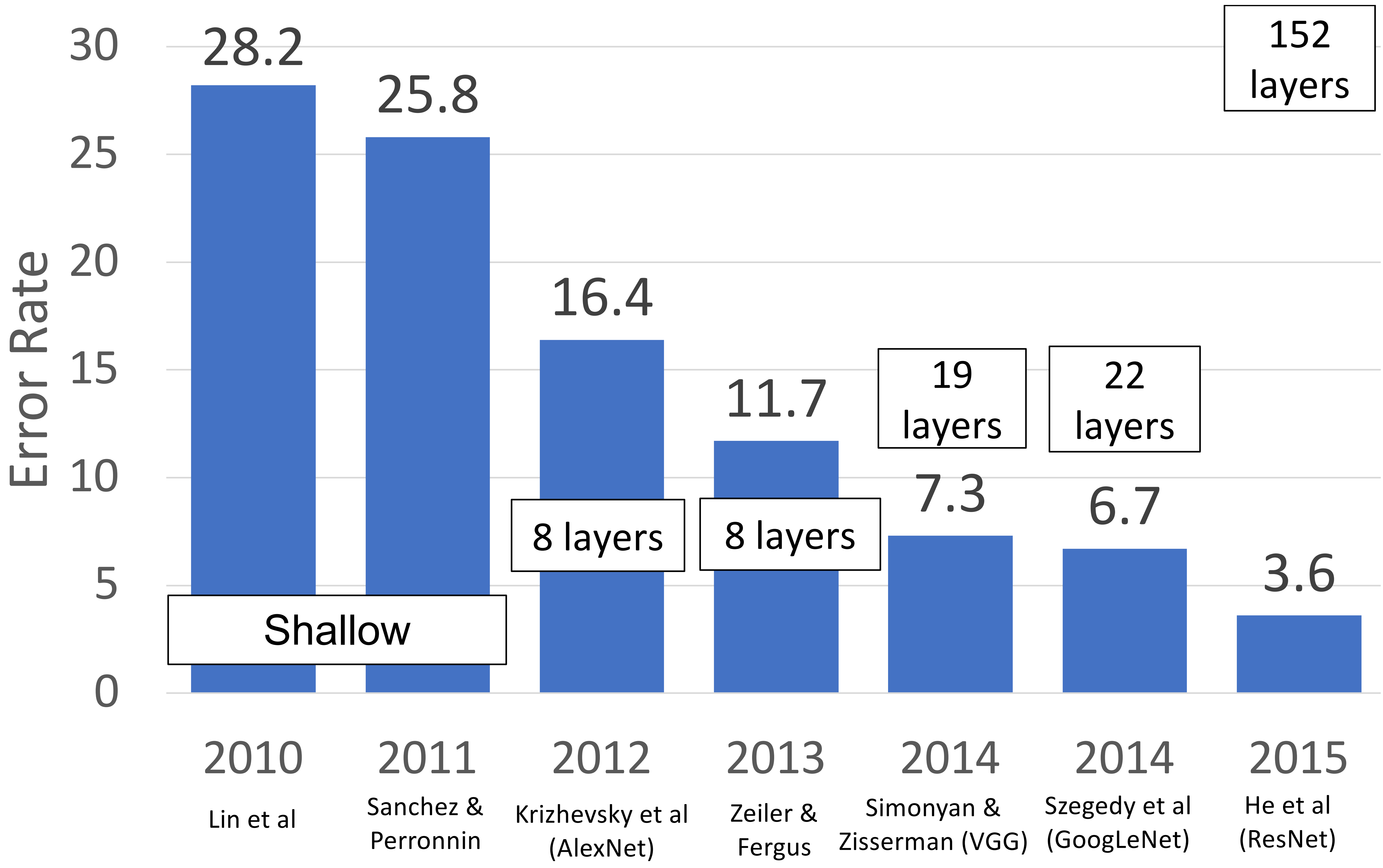
GoogLeNet was before batch normalization! With BatchNorm, we no longer need to use this trick



ImageNet Classification Challenge



ImageNet Classification Challenge

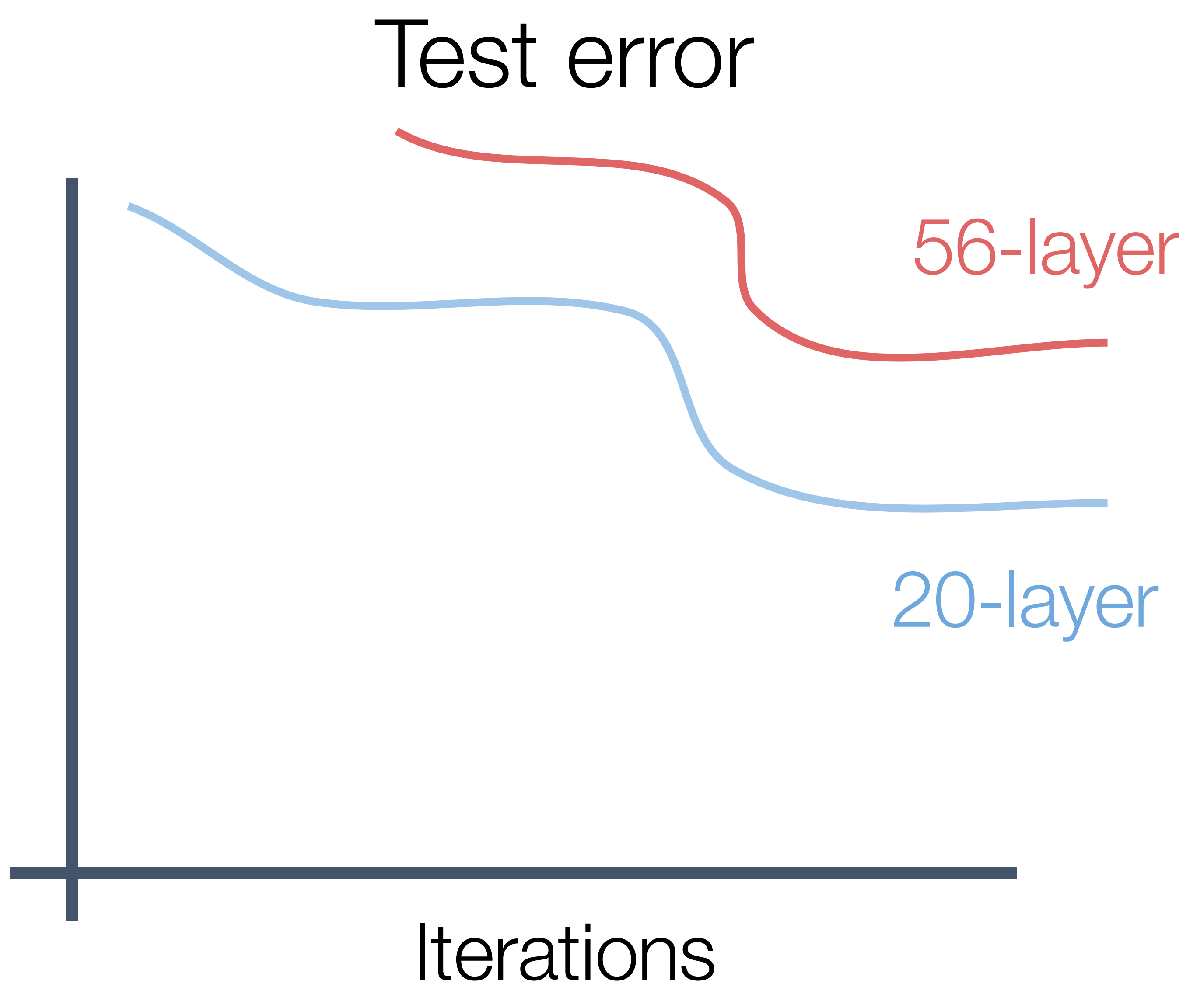


Residual Networks

Once we have Batch Normalization, we can train networks with 10+ layers.
What happens as we go deeper?

Deeper model does worse than shallow model!

Initial guess: Deep model is **overfitting** since
it is much bigger than the other model



He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

Residual Networks

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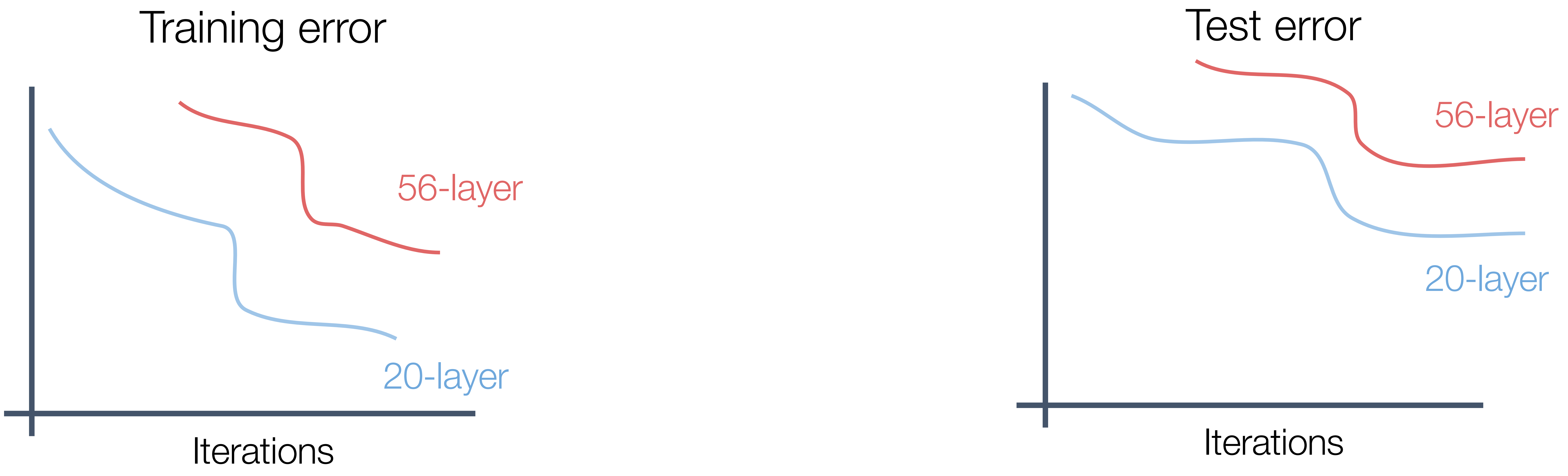
What happens as we go deeper?



In fact the deep model seems to be **underfitting** since it also performs worse than the shallow model on the training set! It is actually **underfitting**

He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

Residual Networks

A deeper model can emulate a shallower model: copy layers from shallower model, set extra layers to identity

Thus deeper models should do at least as good as shallow models

Hypothesis: This is an optimization problem. Deeper models are harder to optimize, and in particular don't learn identity functions to emulate shallow models

He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

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Solution: Change the network so learning identity functions with extra layers is easy!

He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

Residual Networks

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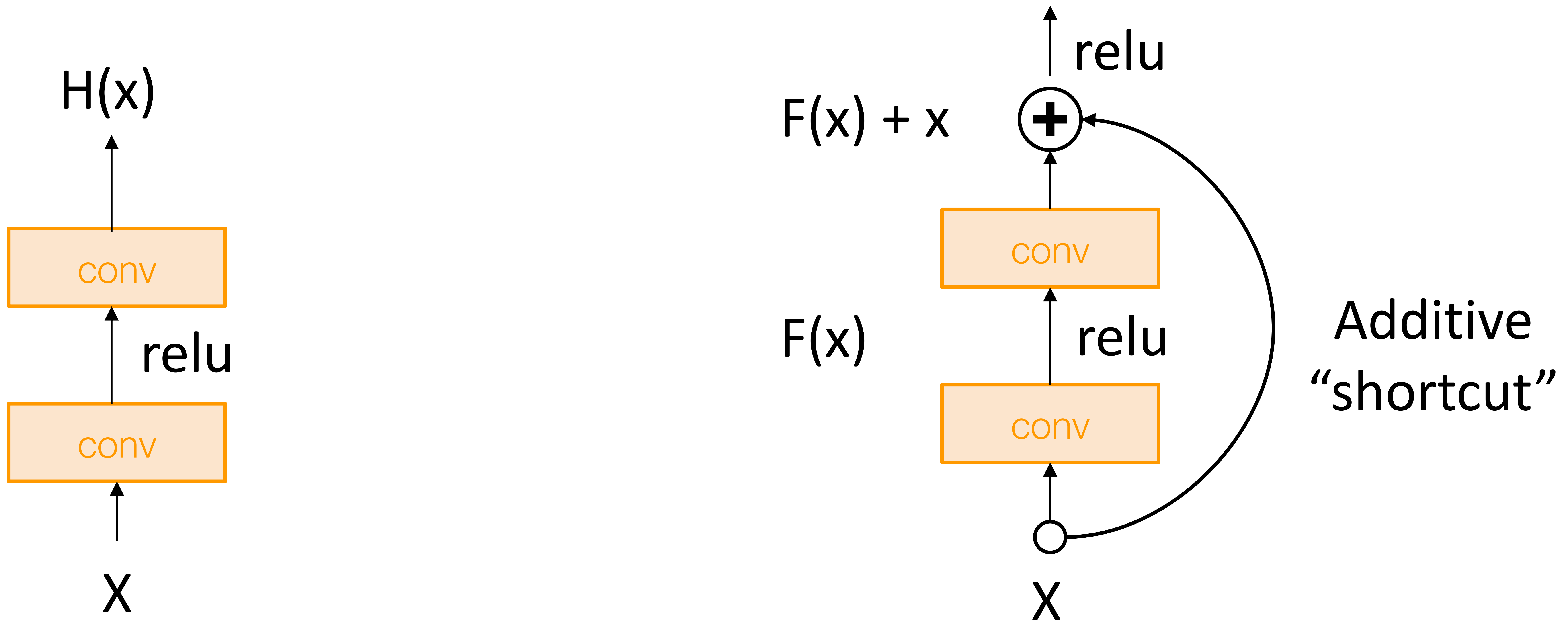


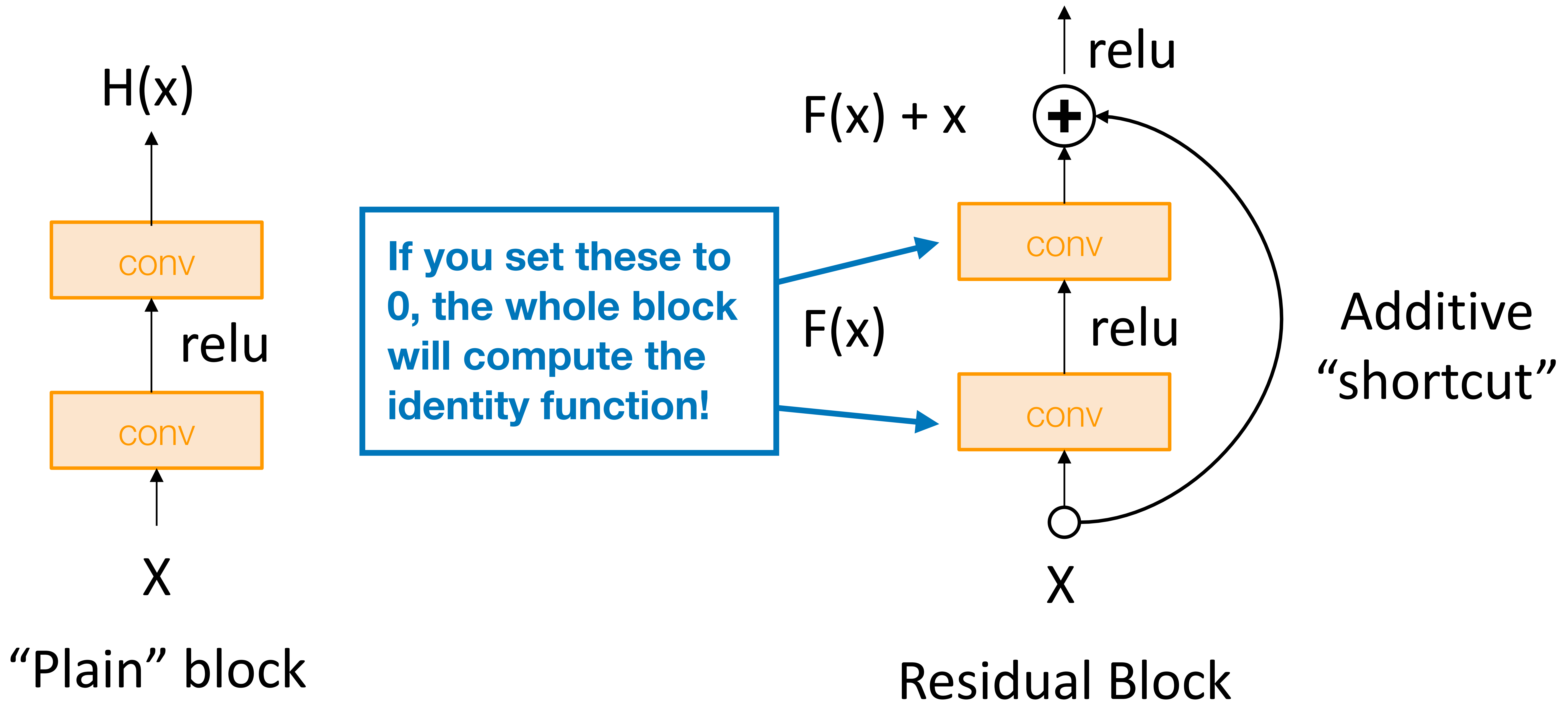
"Plain" block

Residual Block

He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

Residual Networks

Solution: Change the network so learning identity functions with extra layers is easy!



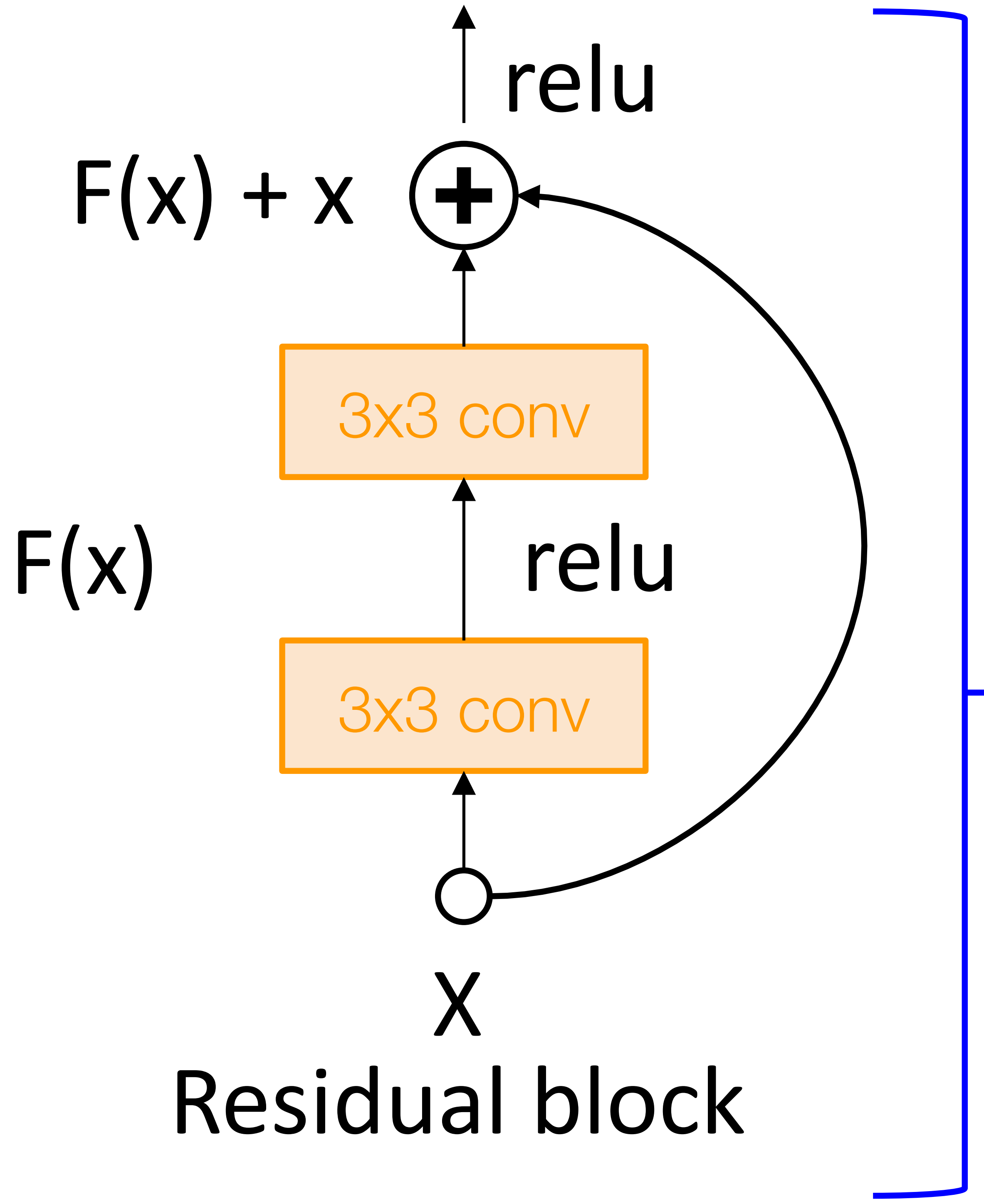
He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

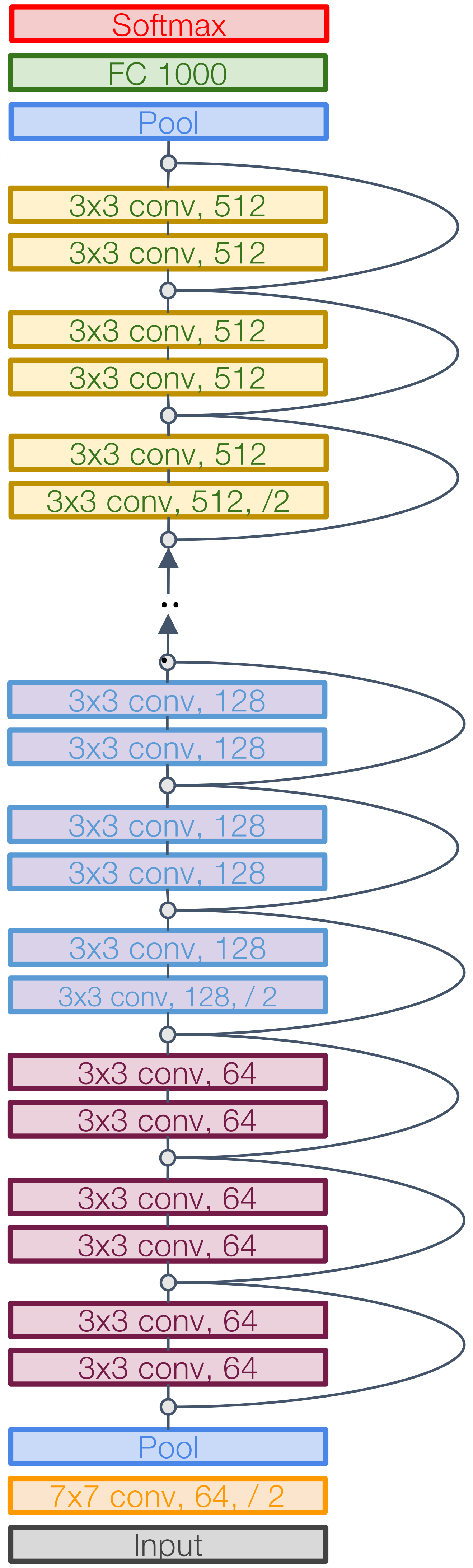
Residual Networks

A residual network is a stack of many residual blocks

Regular design, like VGG: each residual block has two 3x3 conv

Network is divided into **stages**: the first block of each stage halves the resolution (with stride-2 conv) and doubles the number of channels



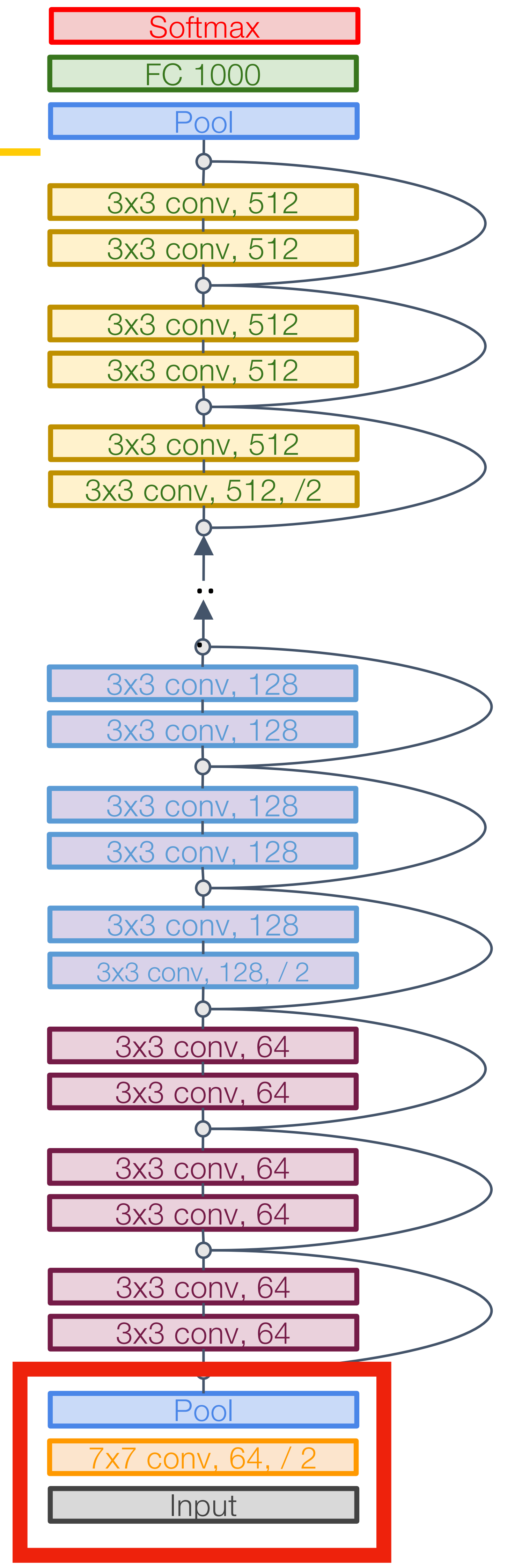


He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

Residual Networks

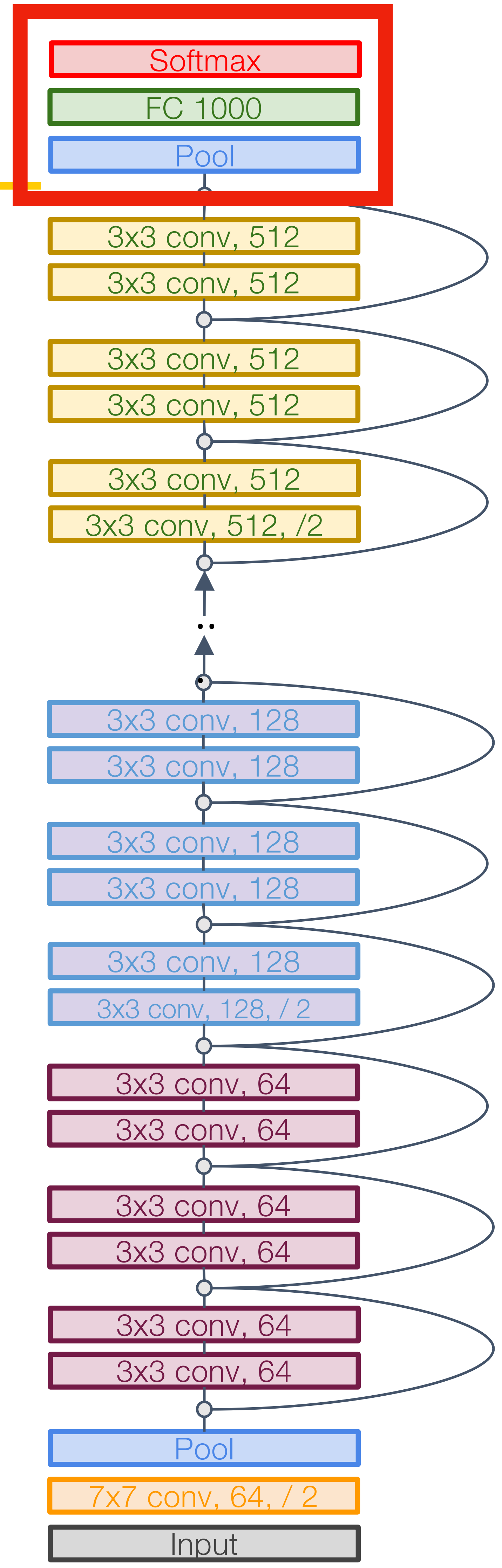
Uses the same aggressive **stem** as GoogleNet to downsample the input 4x before applying residual blocks:

	Input size		Layer				Output size				
Layer	C	H/W	Filters	Kernel	Stride	Pad	C	H/W	Memory (KB)	Params	Flop (M)
Conv	3	224	64	7	2	3	64	112	3136	9	118
Max-pool	64	112		3	2	1	64	56	784	0	2



Residual Networks

Like GoogLeNet, no big fully-connected-layers: Instead use **global average pooling** and a single linear layer at the end

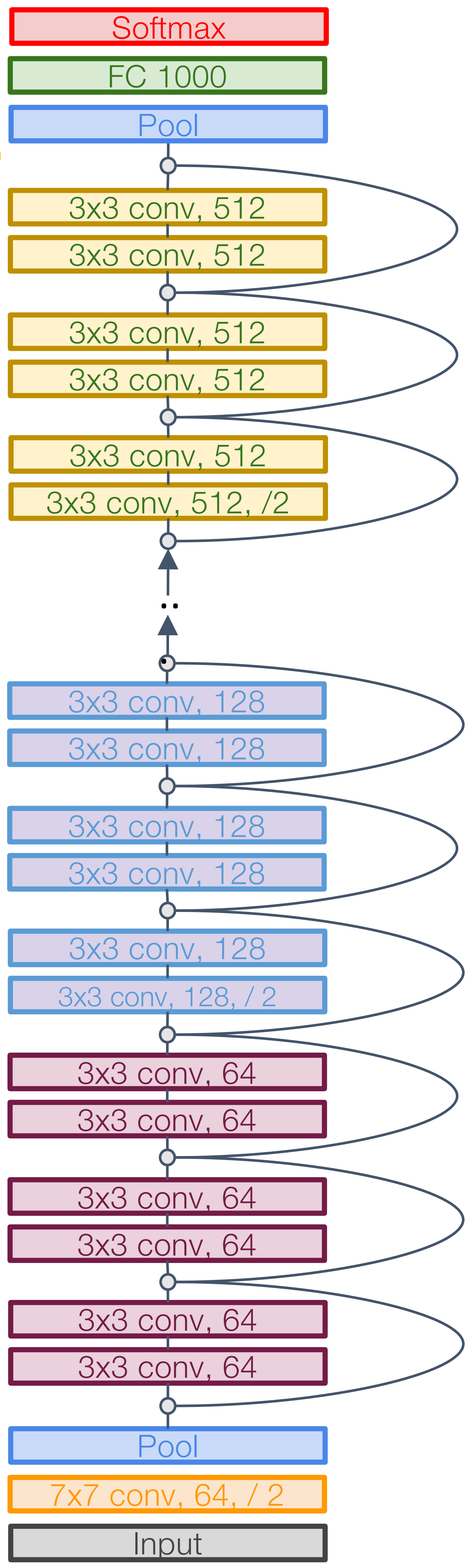


He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

Residual Networks

ResNet-18:
Stem: 1 conv layer
Stage 1 (C=64): 2 res. block = 4 conv
Stage 2 (C=128): 2 res. block = 4 conv
Stage 3 (C=256): 2 res. block = 4 conv
Stage 4 (C=512): 2 res. block = 4 conv
Linear

ImageNet top-5 error: 10.92
GFLOP: 1.8



He et al, "Deep Residual Learning for Image Recognition", CVPR 2016
Error rates are 224x224 single-crop testing, reported by torchvision

Residual Networks

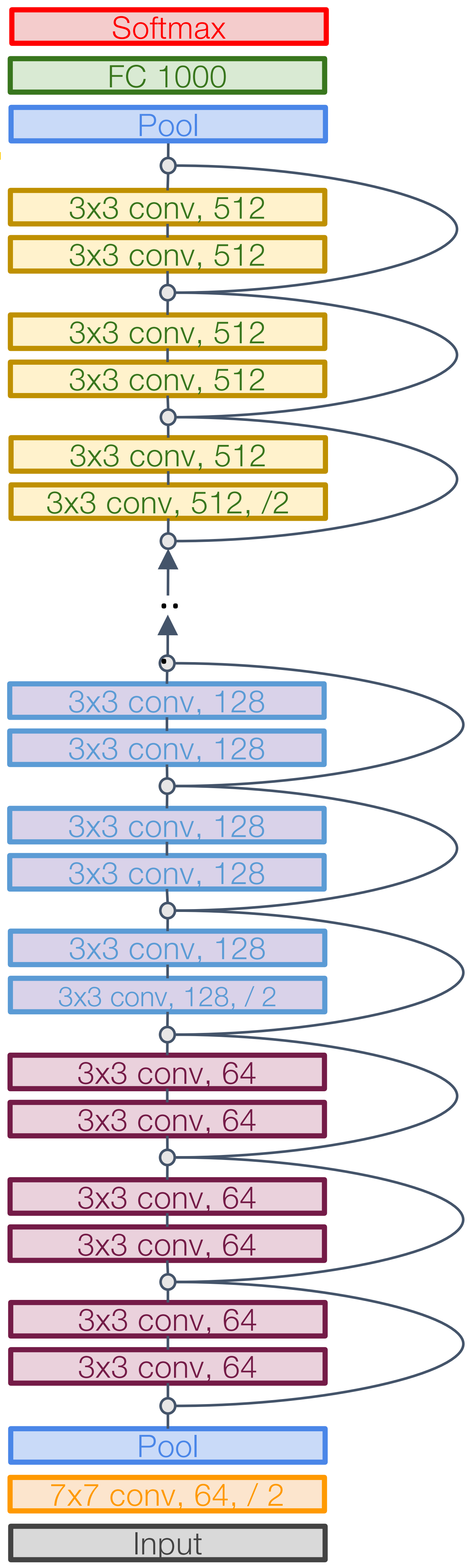
ResNet-18:
Stem: 1 conv layer
Stage 1 (C=64): 2 res. block = 4 conv
Stage 2 (C=128): 2 res. block = 4 conv
Stage 3 (C=256): 2 res. block = 4 conv
Stage 4 (C=512): 2 res. block = 4 conv
Linear

ImageNet top-5 error: 10.92
GFLOP: 1.8

ResNet-34:
Stem: 1 conv layer
Stage 1: 3 res. block = 6 conv
Stage 2: 4 res. block = 8 conv
Stage 3: 6 res. block = 12 conv
Stage 4: 3 res. block = 6 conv
Linear

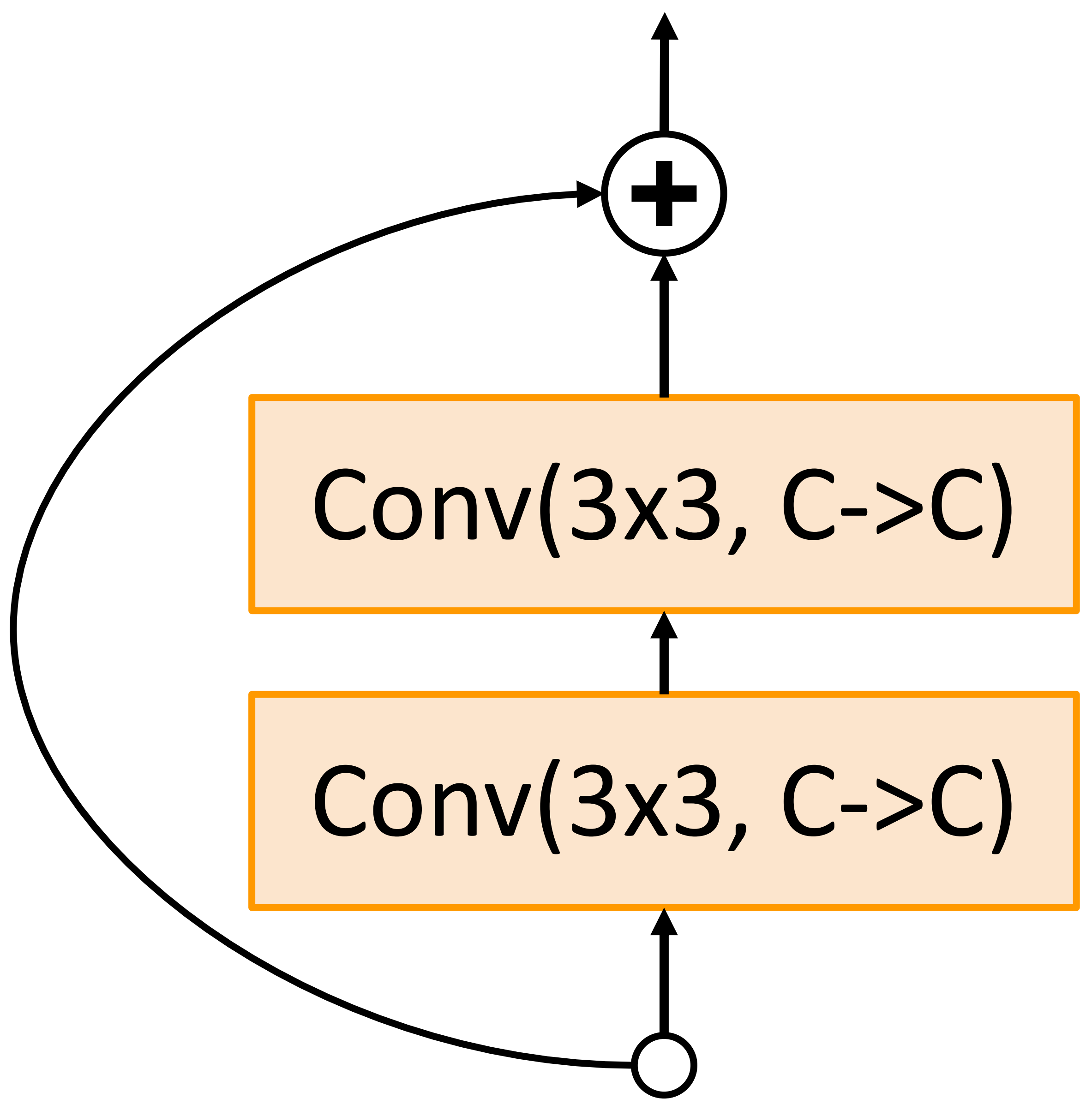
ImageNet top-5 error: 8.58
GFLOP: 3.6

VGG-16:
ImageNet top-5 error: 9.62
GFLOP: 13.6



He et al, "Deep Residual Learning for Image Recognition", CVPR 2016
Error rates are 224x224 single-crop testing, reported by torchvision

Residual Networks: Basic Block



FLOPs: $9HWC^2$

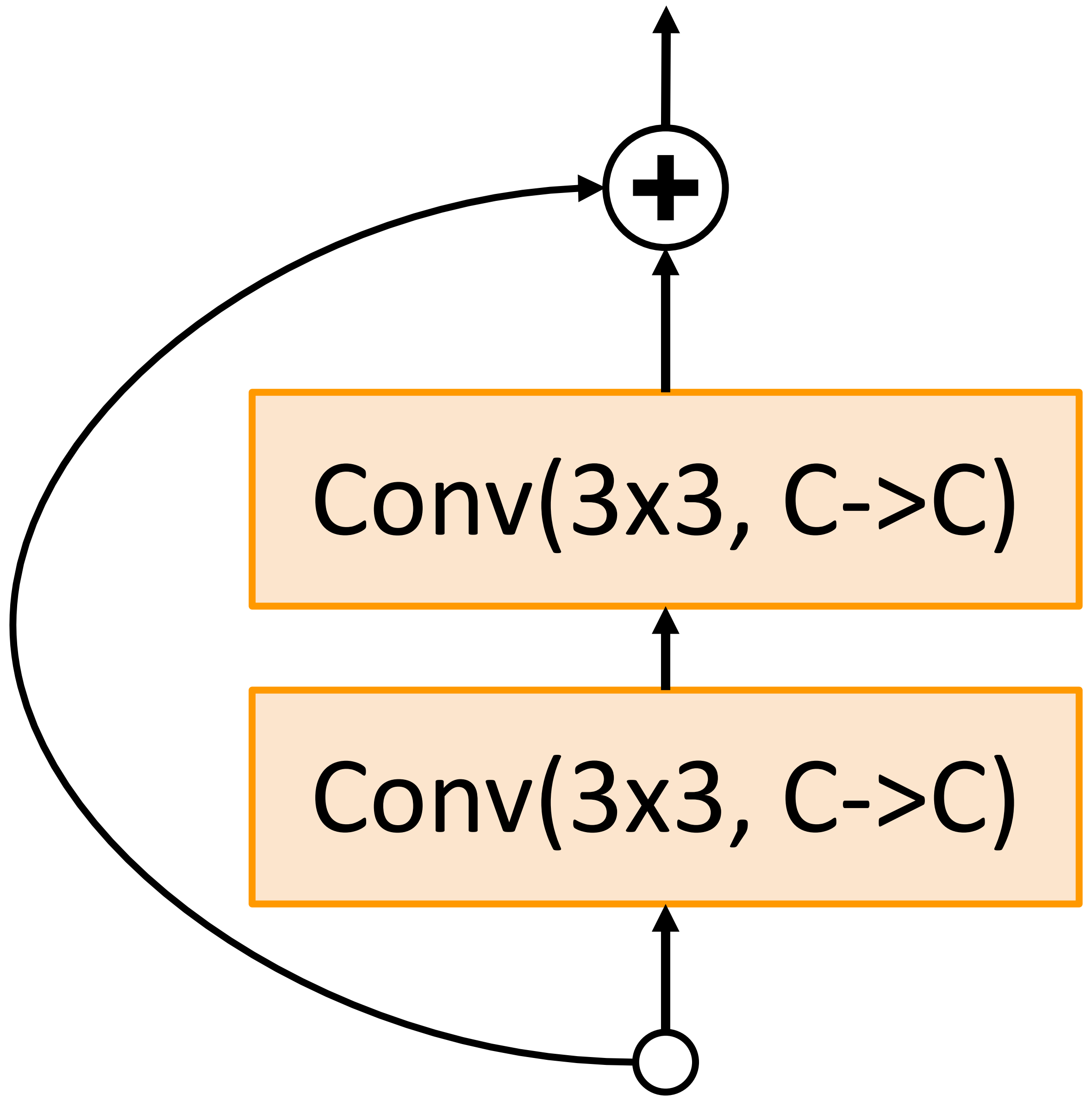
FLOPs: $9HWC^2$

"Basic"
Residual block

Total FLOPs:
$18HWC^2$

He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

Residual Networks: Bottleneck Block

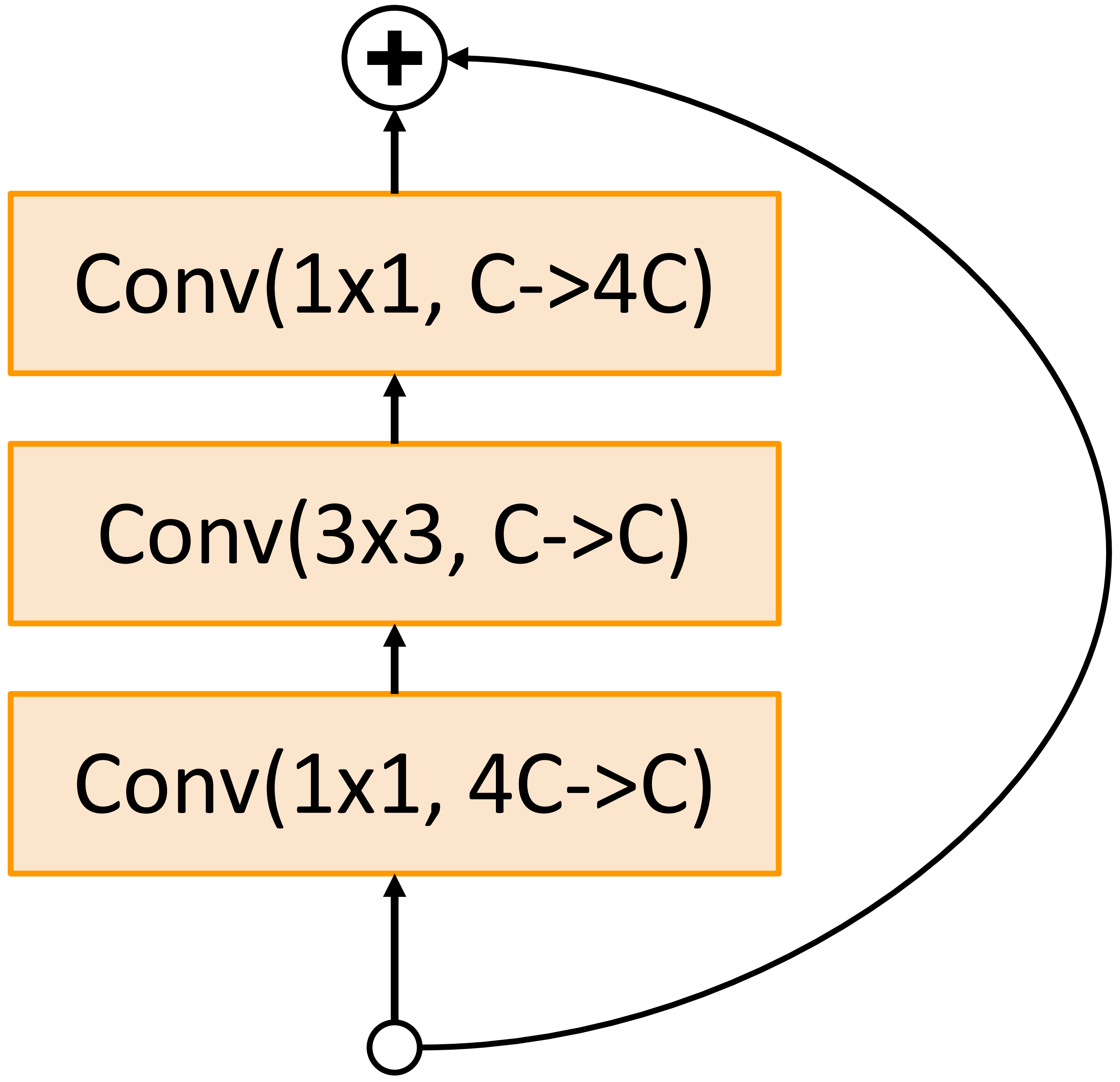


“Basic”
Residual block

FLOPs: $9HWC^2$

FLOPs: $9HWC^2$

Total FLOPs:
$18HWC^2$

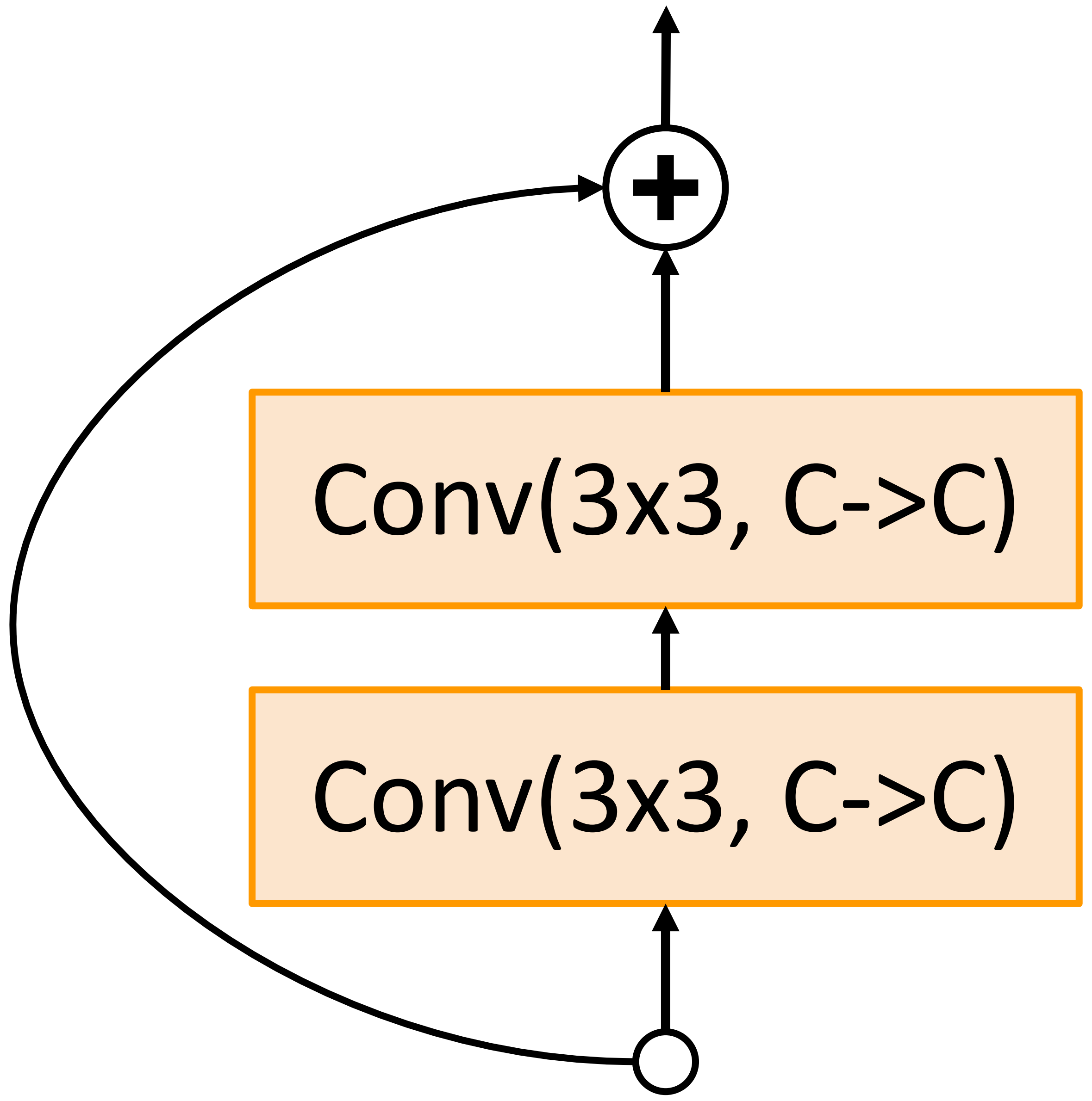


“Bottleneck”
Residual block

He et al, “Deep Residual Learning for Image Recognition”, CVPR 2016

Residual Networks: Bottleneck Block

More layers, less computational cost!

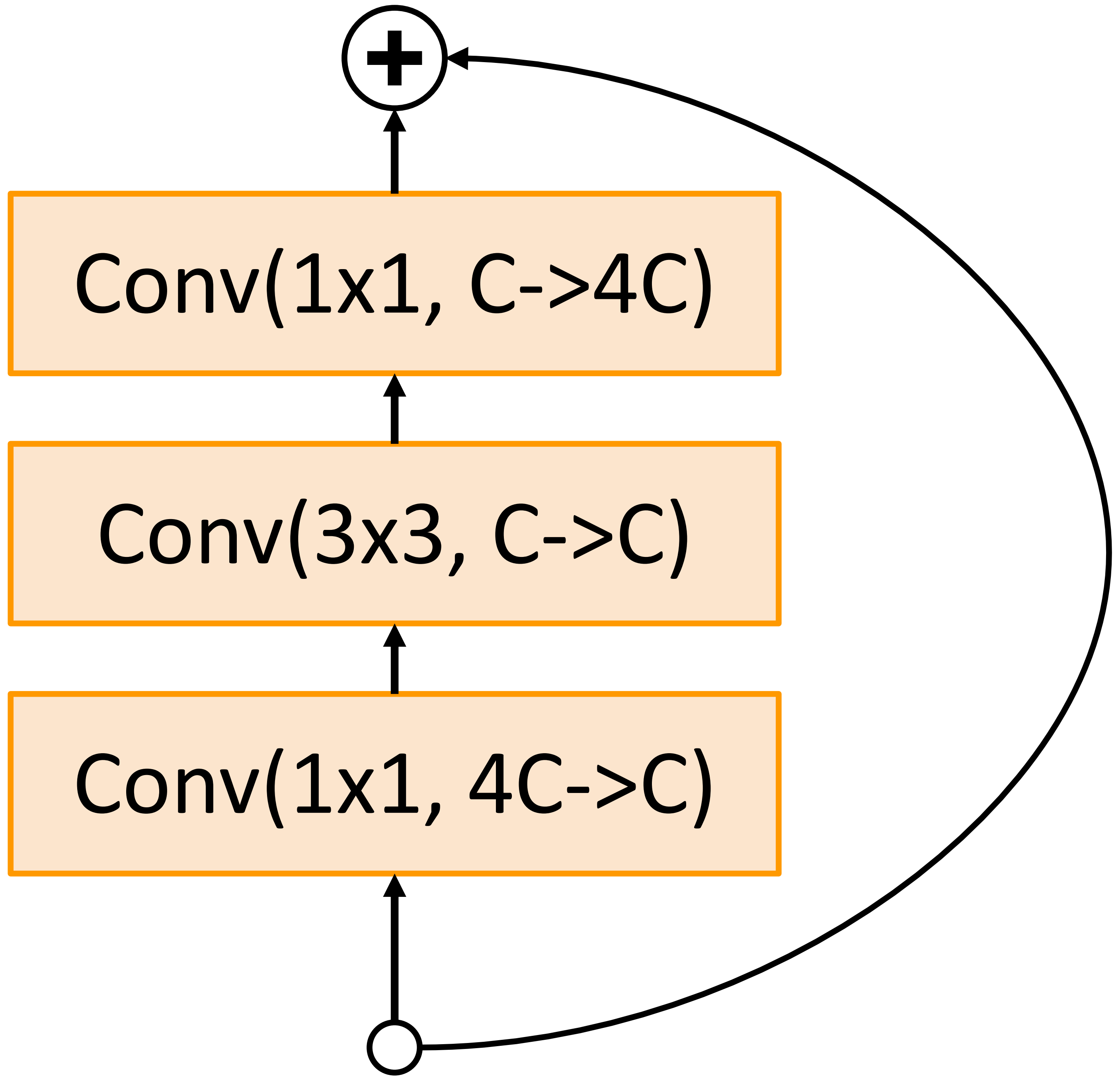


"Basic"
Residual block

FLOPs: $9HWC^2$

FLOPs: $9HWC^2$

Total FLOPs:
$18HWC^2$



FLOPs: $4HWC^2$

FLOPs: $9HWC^2$

FLOPs: $4HWC^2$

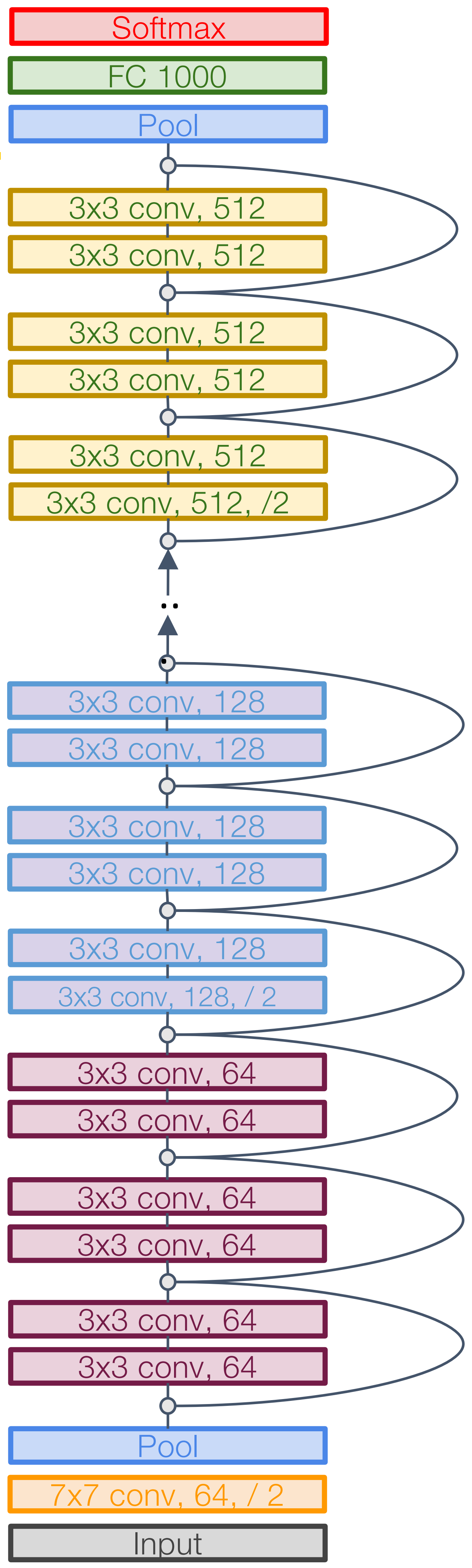
Total FLOPs:
$17HWC^2$

"Bottleneck"
Residual block

He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

Residual Networks

			Stage 1		Stage 2		Stage 3		Stage 4				
	Block type	**Stem layers**	**Blocks**	**Layers**	**Blocks**	**Layers**	**Blocks**	**Layers**	**Blocks**	**Layers**	**FC Layers**	**GFLOP**	**ImageNet**
ResNet-18	Basic	1	2	4	2	4	2	4	2	4	1	1.8	10.92
ResNet-34	Basic	1	3	6	4	8	6	12	3	6	1	3.6	8.58

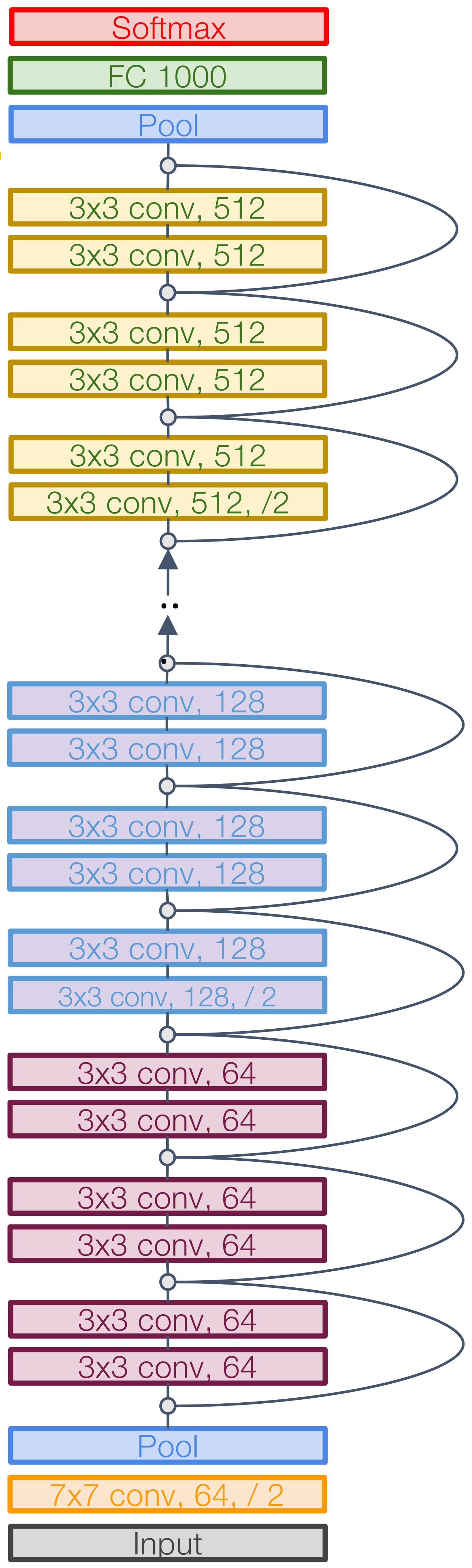


He et al, "Deep Residual Learning for Image Recognition", CVPR 2016
Error rates are 224x224 single-crop testing, reported by torchvision

Residual Networks

ResNet-50 is the same as ResNet-34, but replaces Basic blocks with Bottleneck Blocks. This is a great baseline architecture for many tasks even today!

			Stage 1		Stage 2		Stage 3		Stage 4				
	Block type	Stem layers	Blocks	Layers	Blocks	Layers	Blocks	Layers	Blocks	Layers	FC Layers	GFLOP	ImageNet
ResNet-18	Basic	1	2	4	2	4	2	4	2	4	1	1.8	10.92
ResNet-34	Basic	1	3	6	4	8	6	12	3	6	1	3.6	8.58
ResNet-50	Bottle	1	3	9	4	12	6	18	3	9	1	3.8	7.13

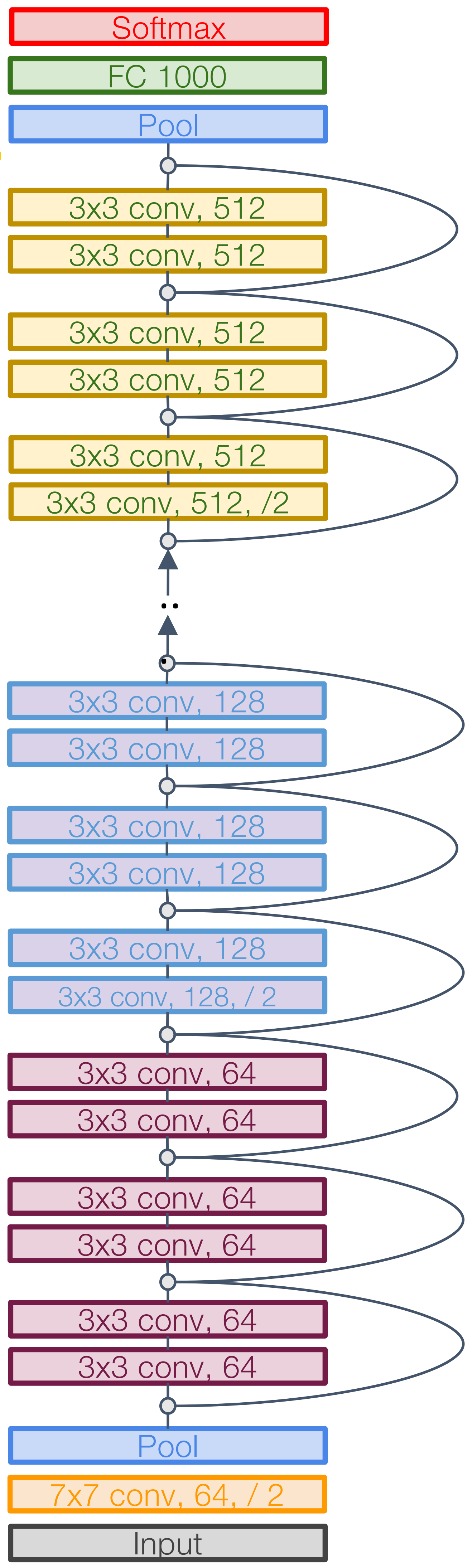


He et al, "Deep Residual Learning for Image Recognition", CVPR 2016
Error rates are 224x224 single-crop testing, reported by torchvision

Residual Networks

Deeper ResNet-101 and ResNet-152 models are more accurate, but also more computationally heavy

			Stage 1		Stage 2		Stage 3		Stage 4				
	Block type	**Stem layers**	**Blocks**	**Layers**	**Blocks**	**Layers**	**Blocks**	**Layers**	**Blocks**	**Layers**	**FC Layers**	**GFLOP**	**ImageNet**
ResNet-18	Basic	1	2	4	2	4	2	4	2	4	1	1.8	10.92
ResNet-34	Basic	1	3	6	4	8	6	12	3	6	1	3.6	8.58
ResNet-50	Bottle	1	3	9	4	12	6	18	3	9	1	3.8	7.13
ResNet-101	Bottle	1	3	9	4	12	23	69	3	9	1	7.6	6.44
ResNet-152	Bottle	1	3	9	8	24	36	108	3	9	1	11.3	5.94



He et al, "Deep Residual Learning for Image Recognition", CVPR 2016
Error rates are 224x224 single-crop testing, reported by torchvision

Residual Networks

- Able to train very deep networks
- Deeper networks do better than shallow networks (as expected)
- Swept 1st place in all ILSVRC and COCO 2015 competitions
- Still widely used today

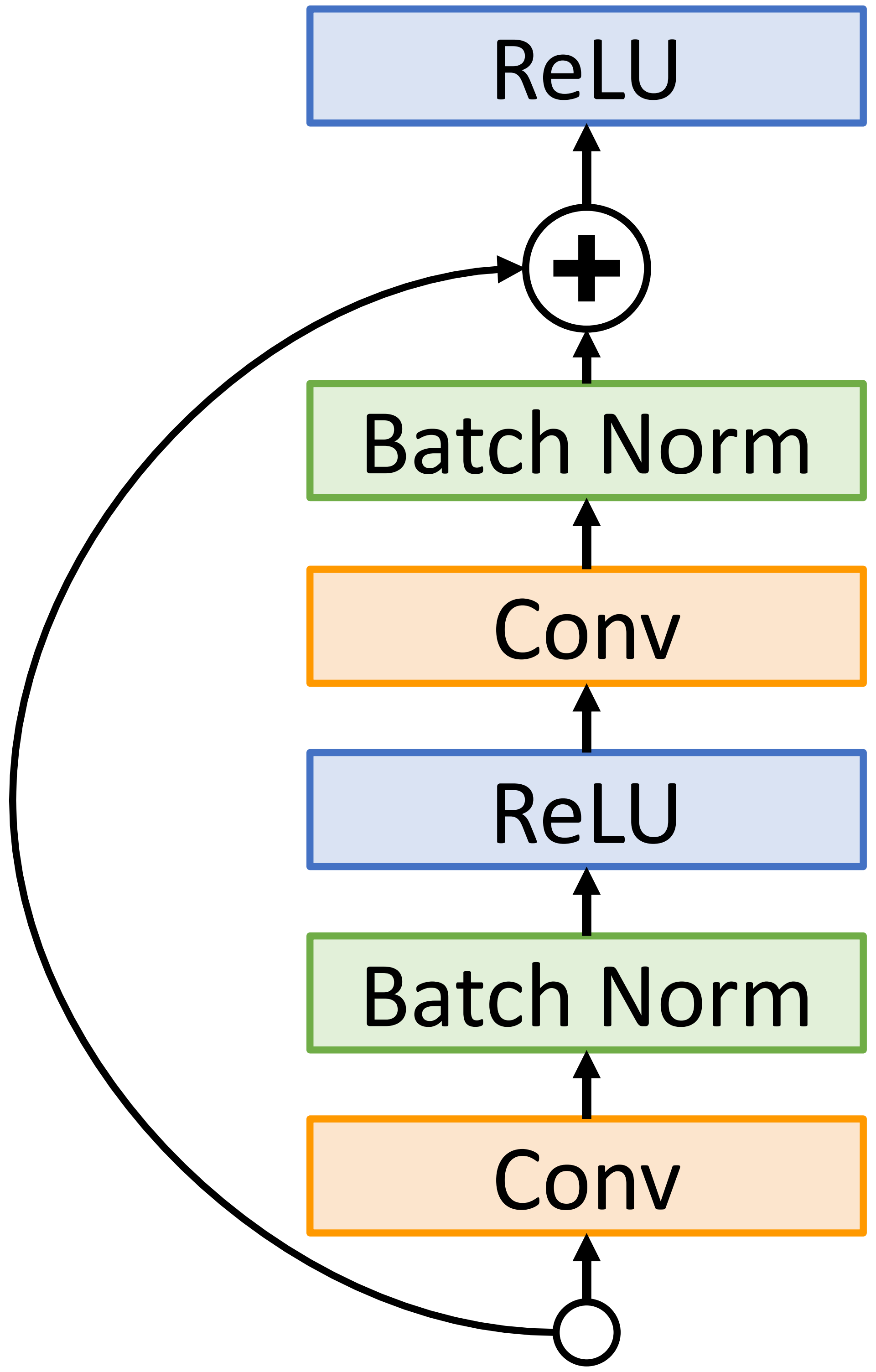
MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

He et al, "Deep Residual Learning for Image Recognition", CVPR 2016

Improving Residual Networks: Block Design

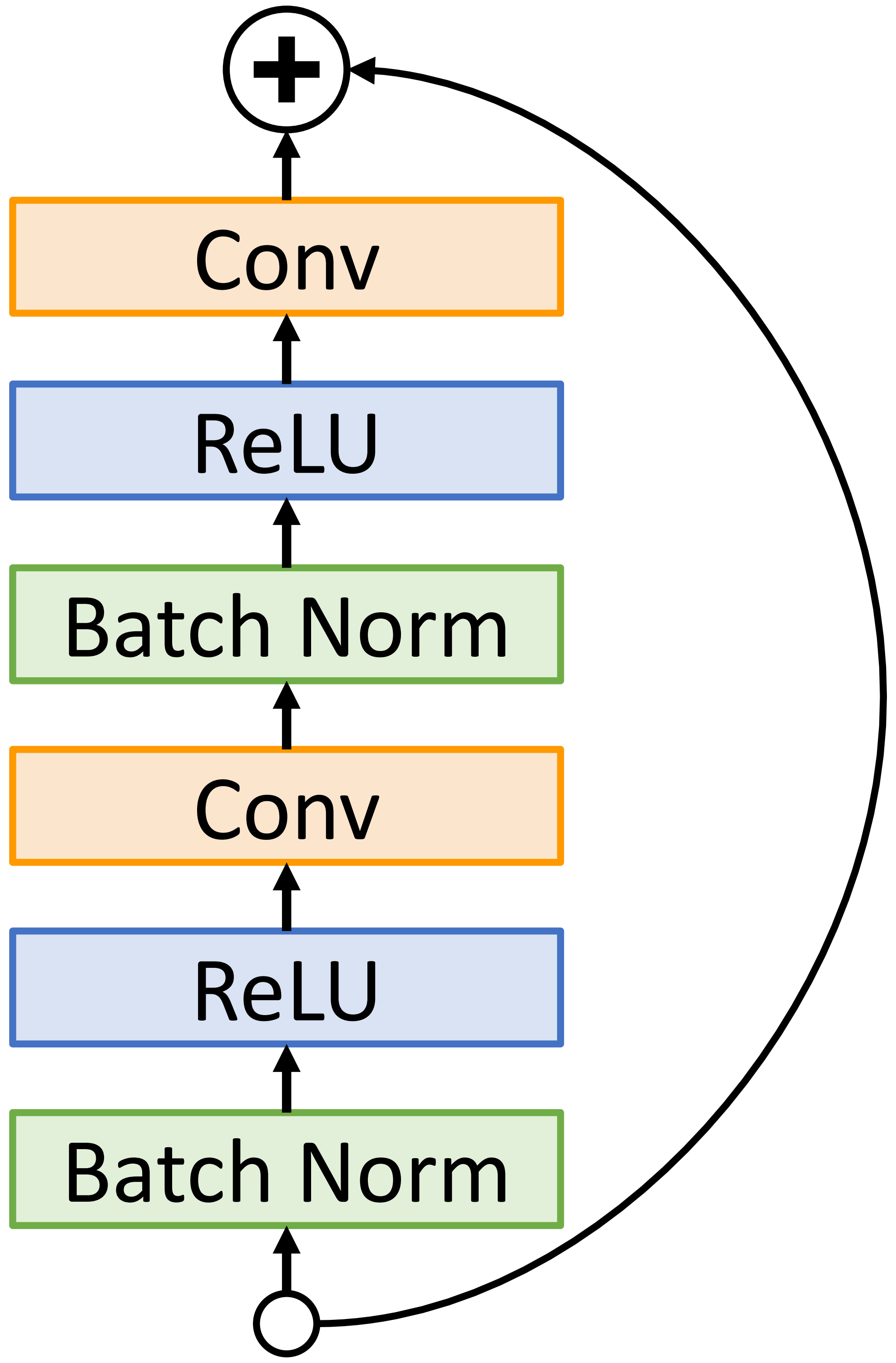
Original ResNet block



Note ReLU **after** residual:

Cannot actually learn identity function since outputs are nonnegative!

"Pre-Activation" ResNet Block



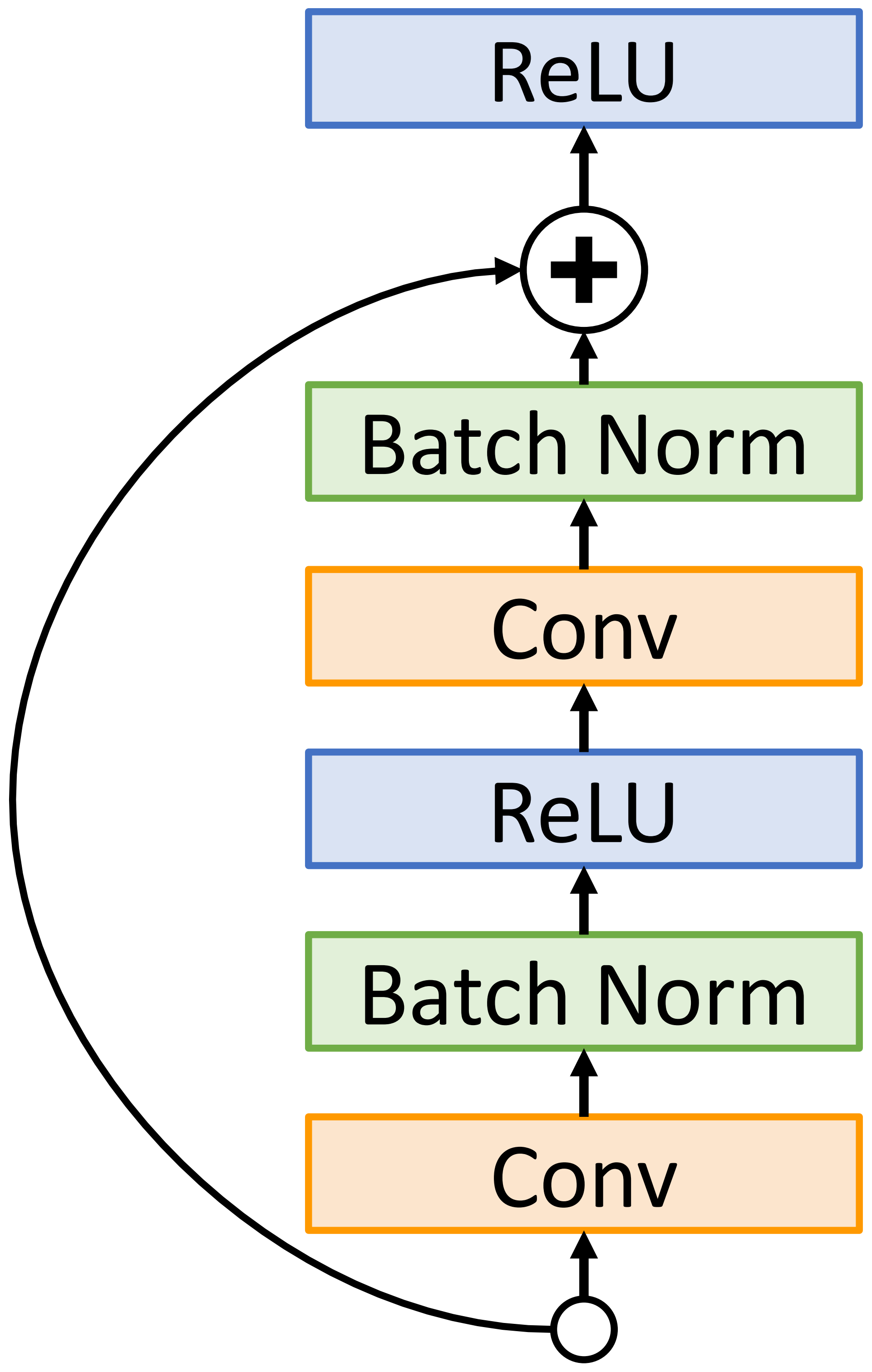
Note ReLU **inside** residual:

Can learn identity function by setting Conv weights to zero

He et al, "Identity mappings in deep residual networks", ECCV 2016

Improving Residual Networks: Block Design

Original ResNet block

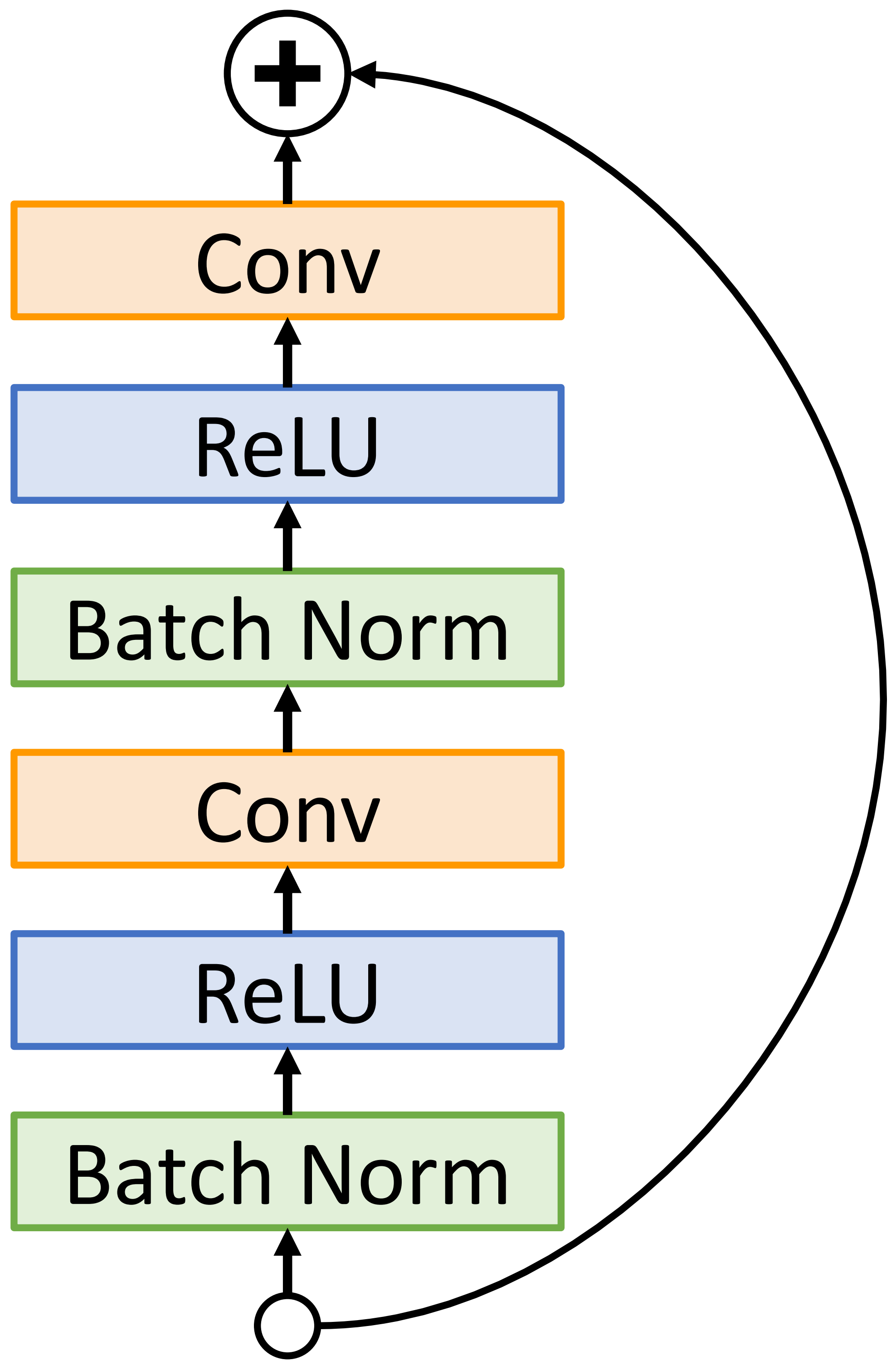


Slight improvement in accuracy (ImageNet top-1 error)

ResNet-152: 21.3 vs **21.1**
ResNet-200: 21.8 vs **20.7**

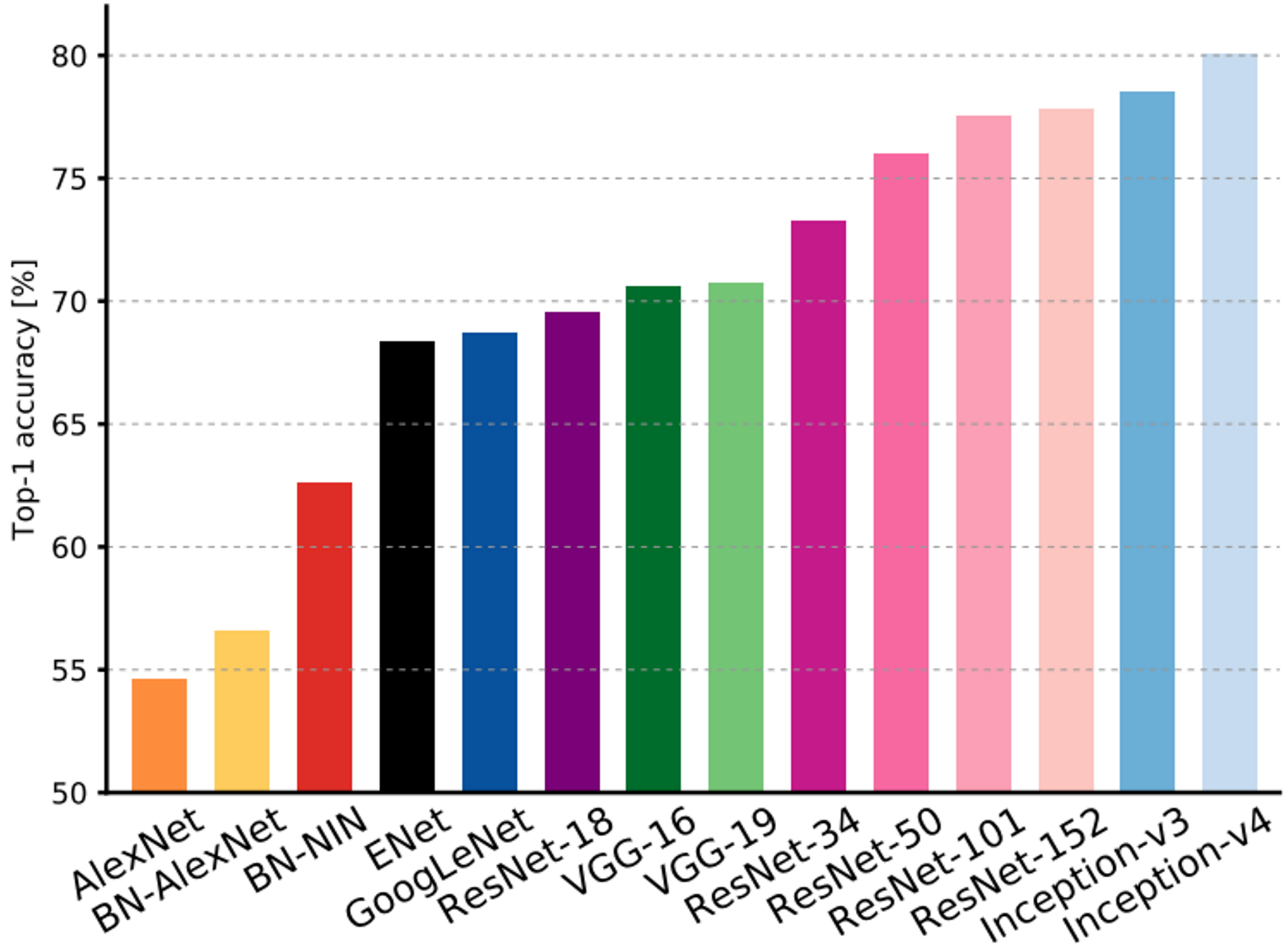
Not actually used that much in practice

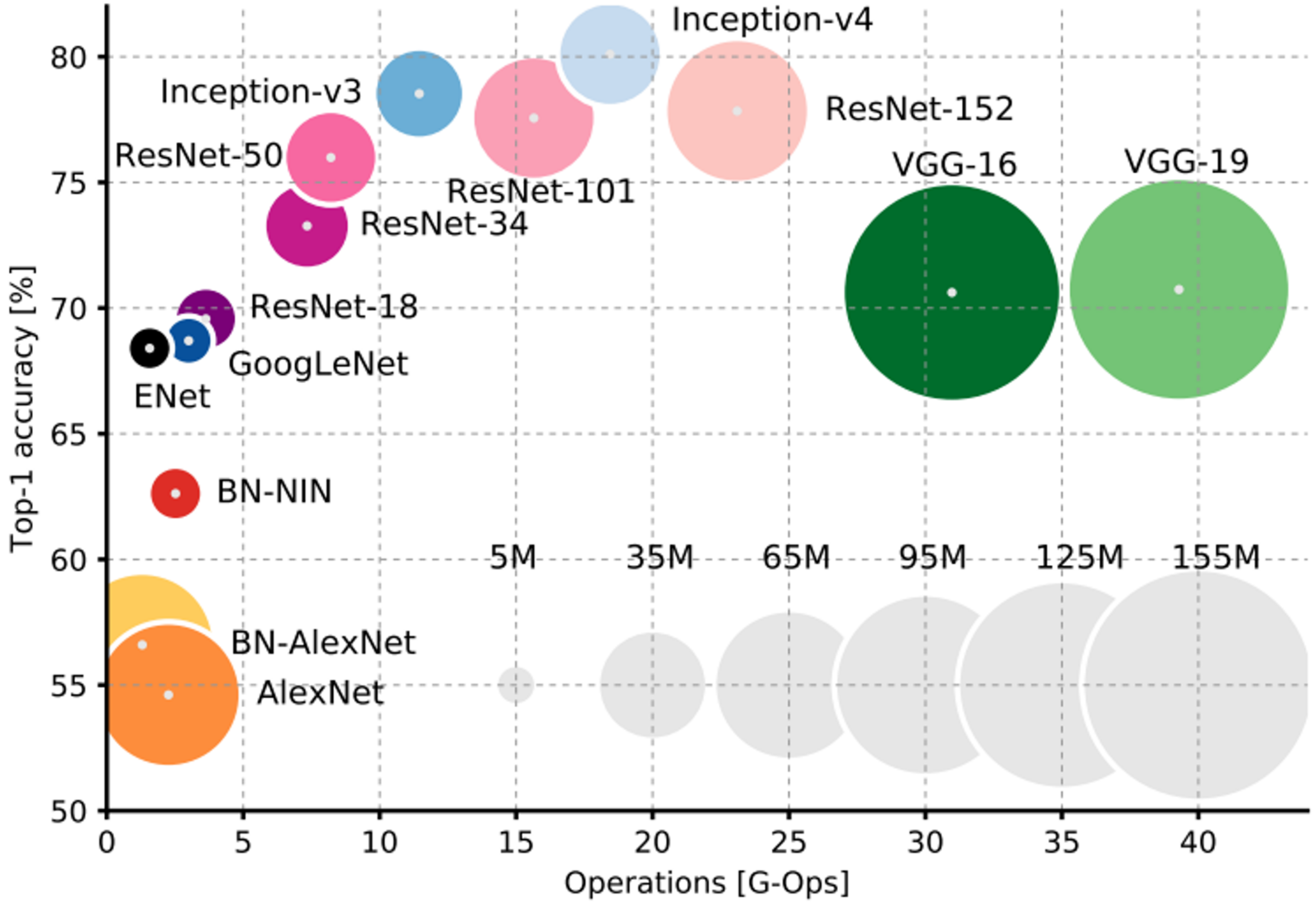
"Pre-Activation" ResNet Block



He et al, "Identity mappings in deep residual networks", ECCV 2016

Comparing Complexity

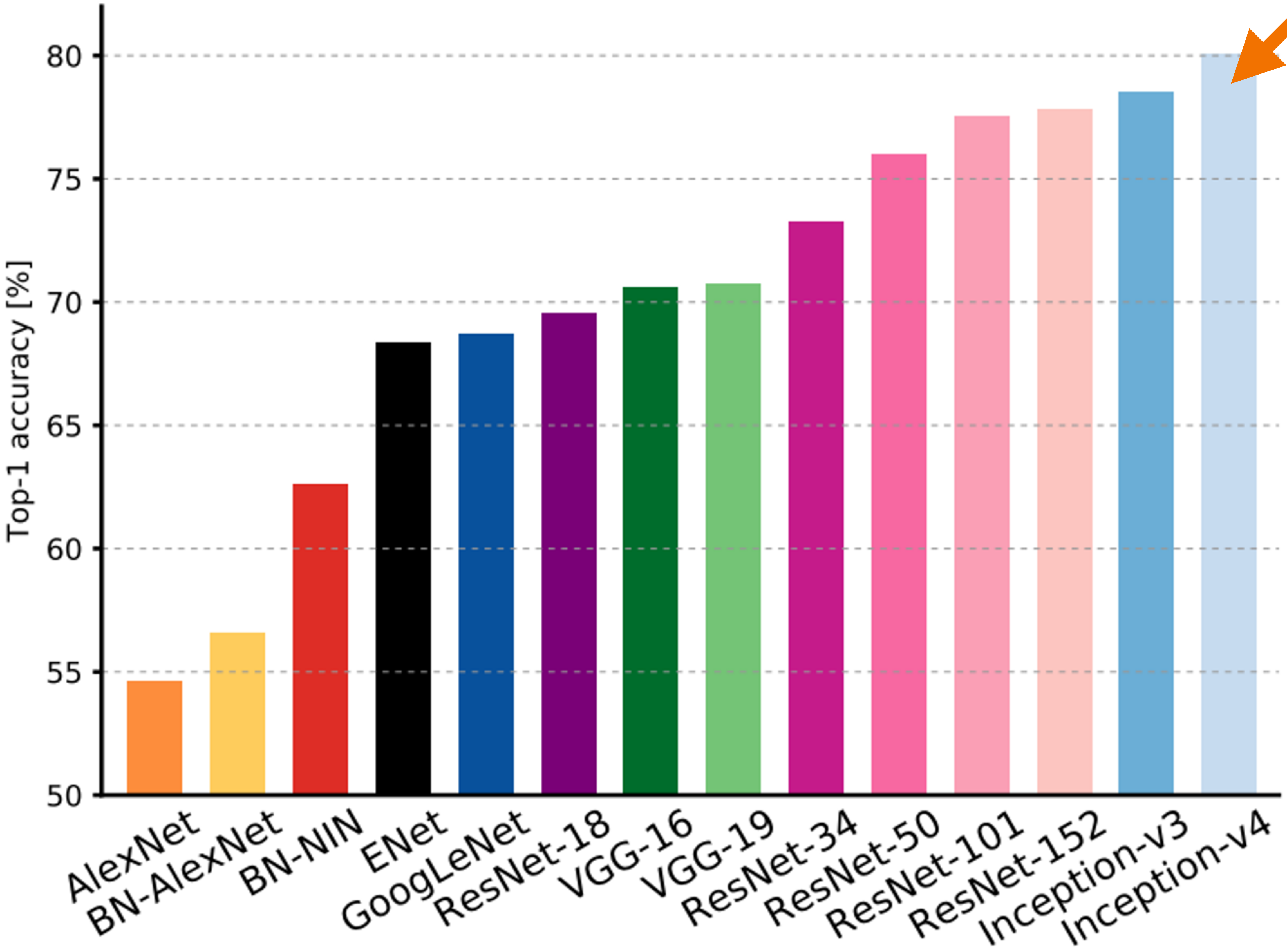


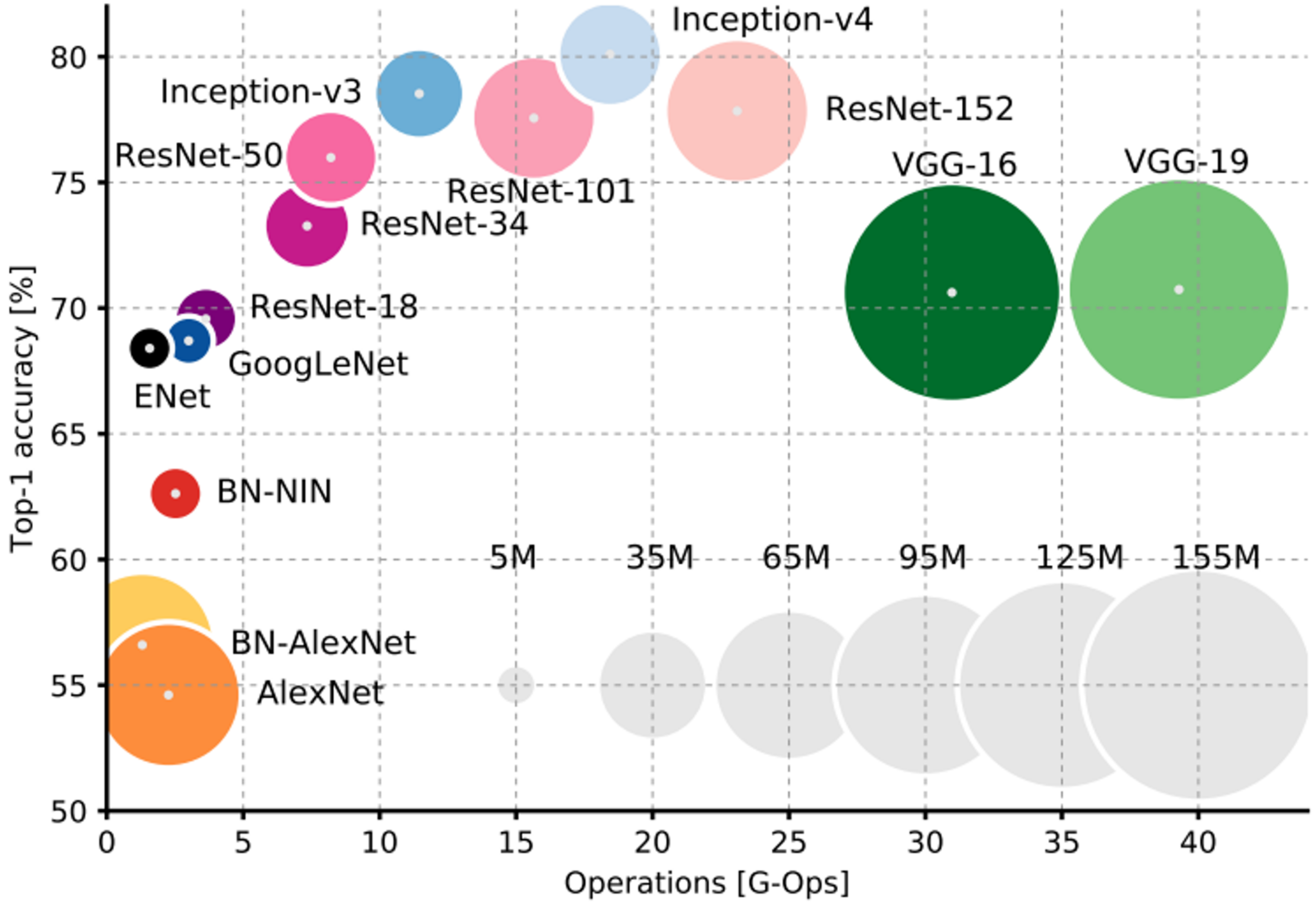


Canziani et al, "An analysis of deep neural network models for practical applications", 2017

Comparing Complexity

Inception-v4: ResNet + Inception!

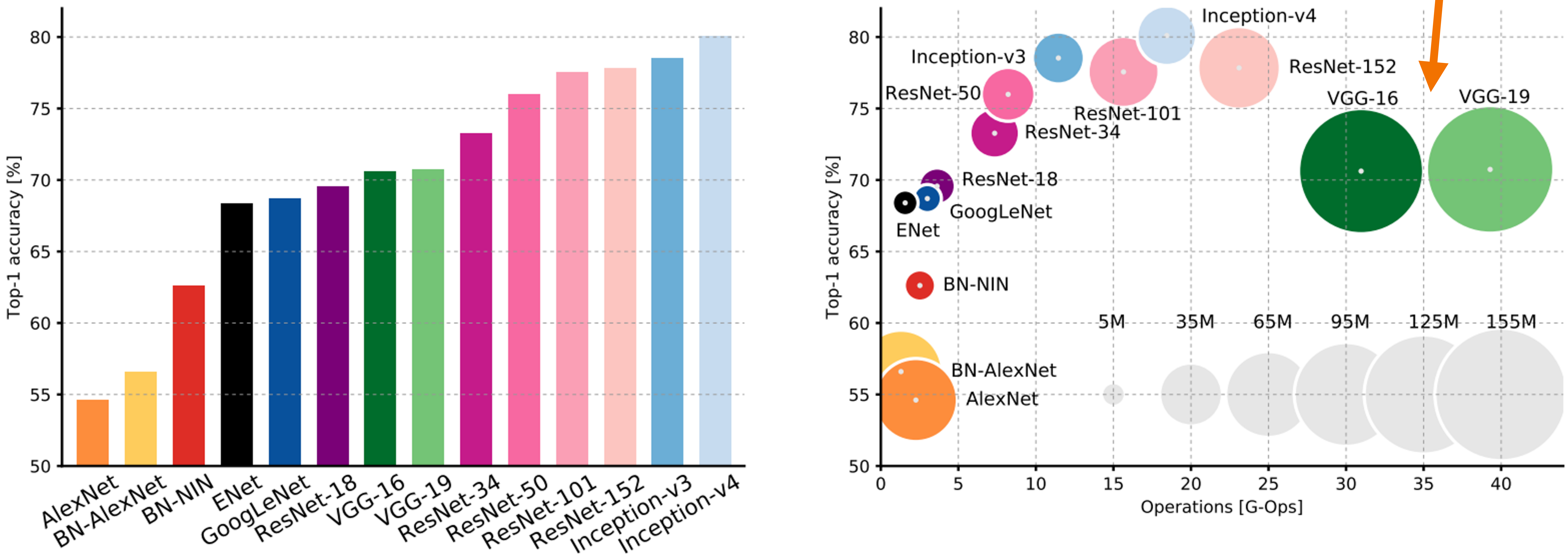




Canziani et al, “An analysis of deep neural network models for practical applications”, 2017

Comparing Complexity

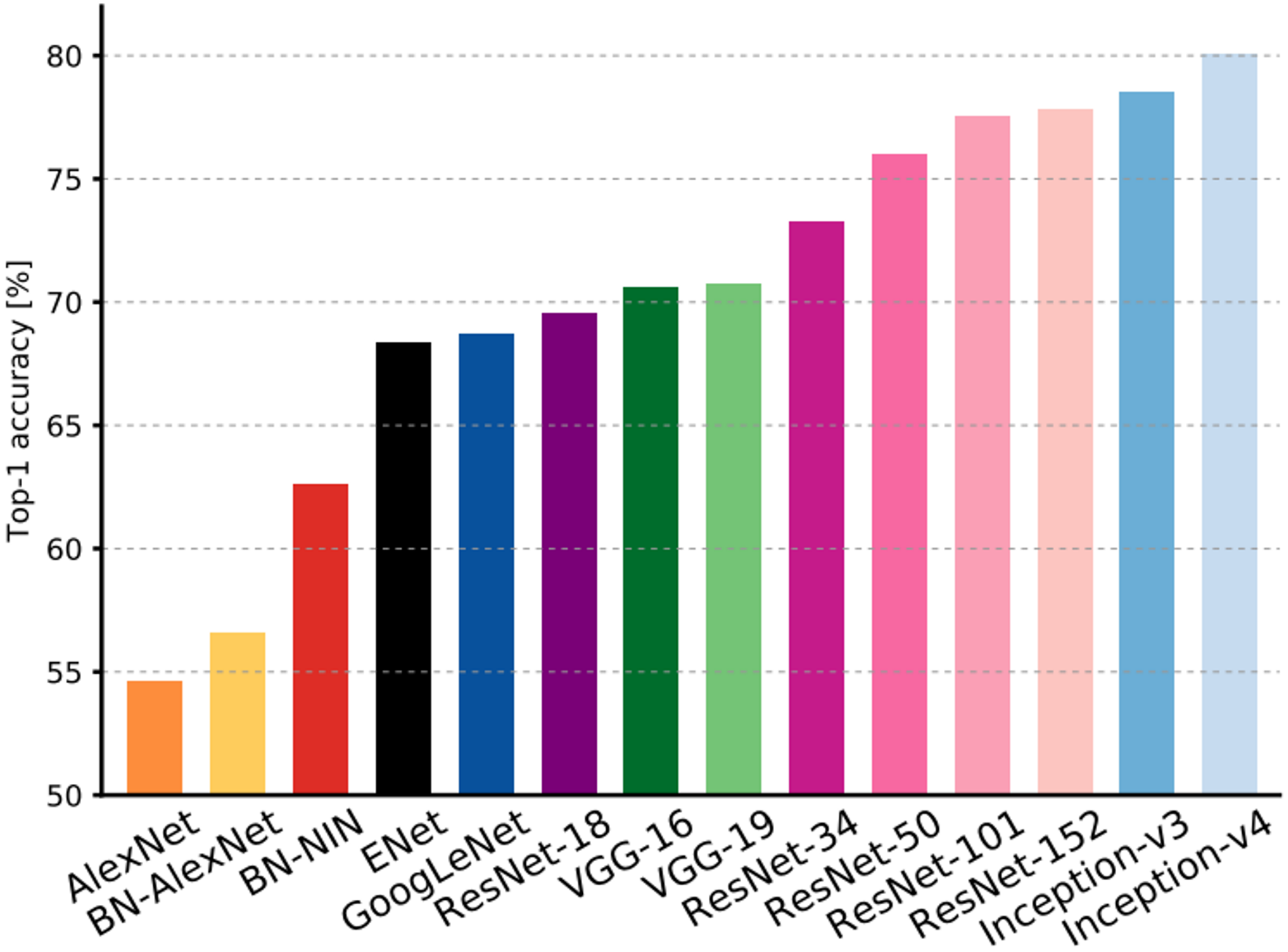
**VGG:
Highest memory,
most operations**

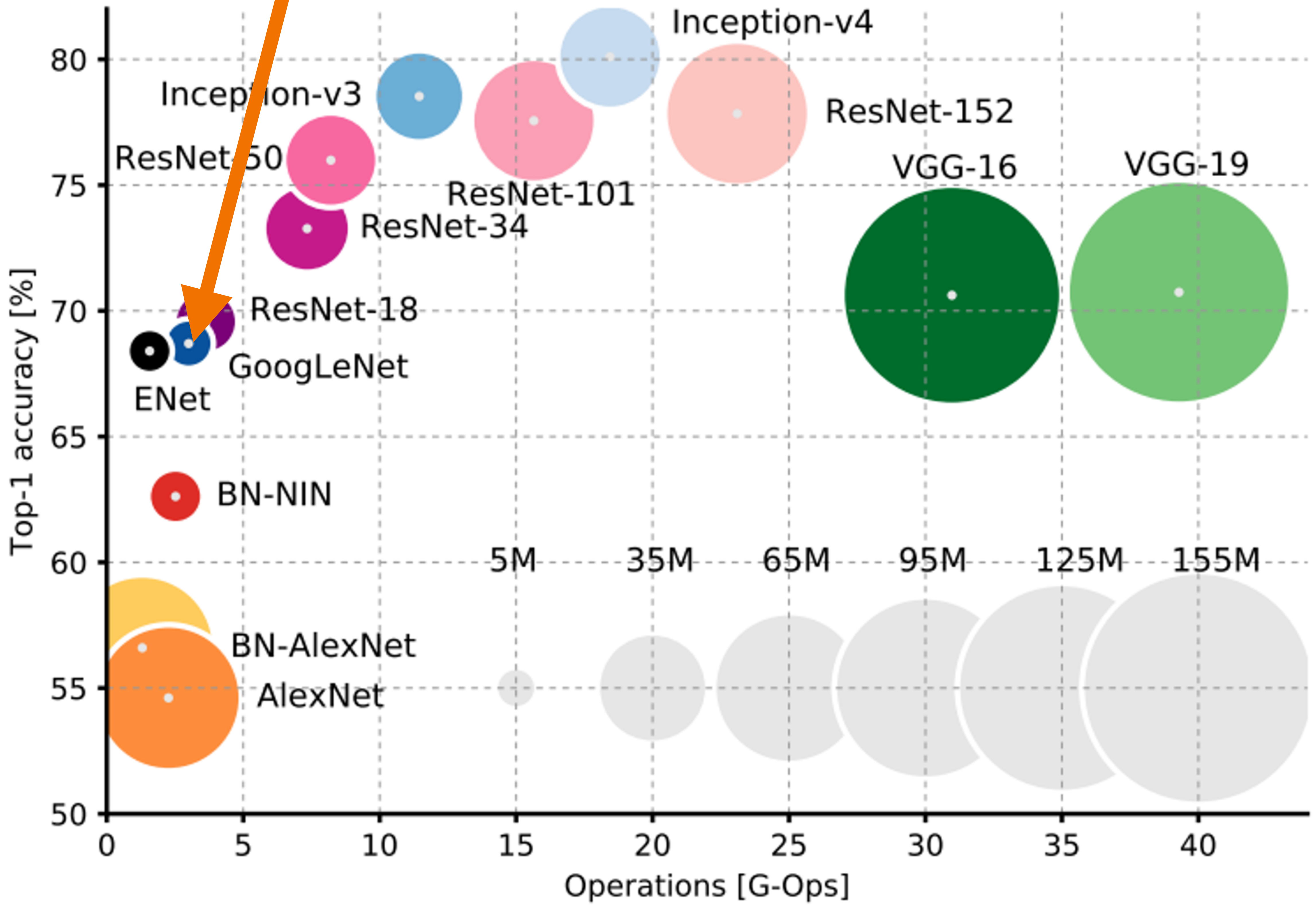


Canziani et al, "An analysis of deep neural network models for practical applications", 2017

Comparing Complexity

GoogLeNet:
Very efficient!

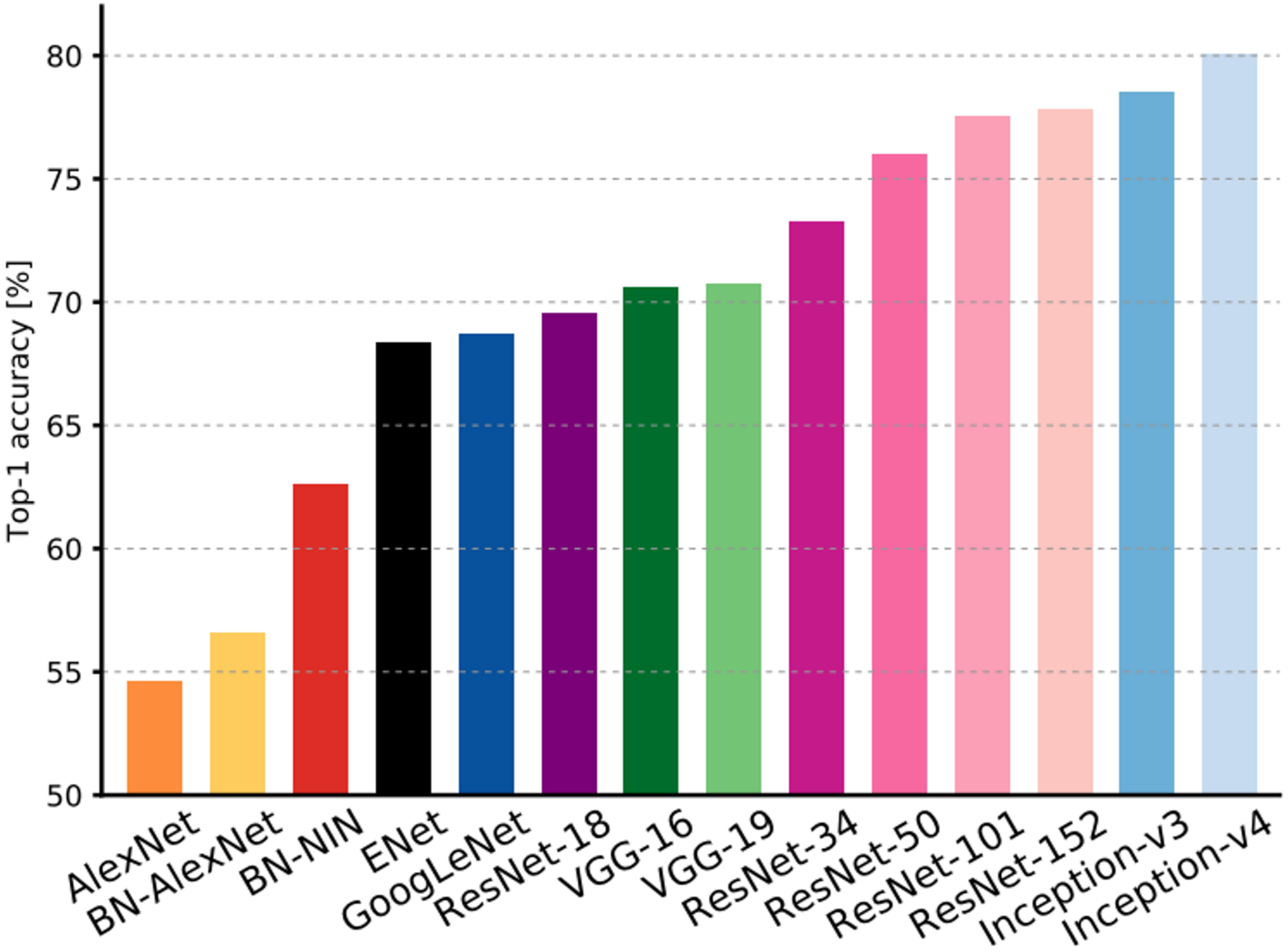


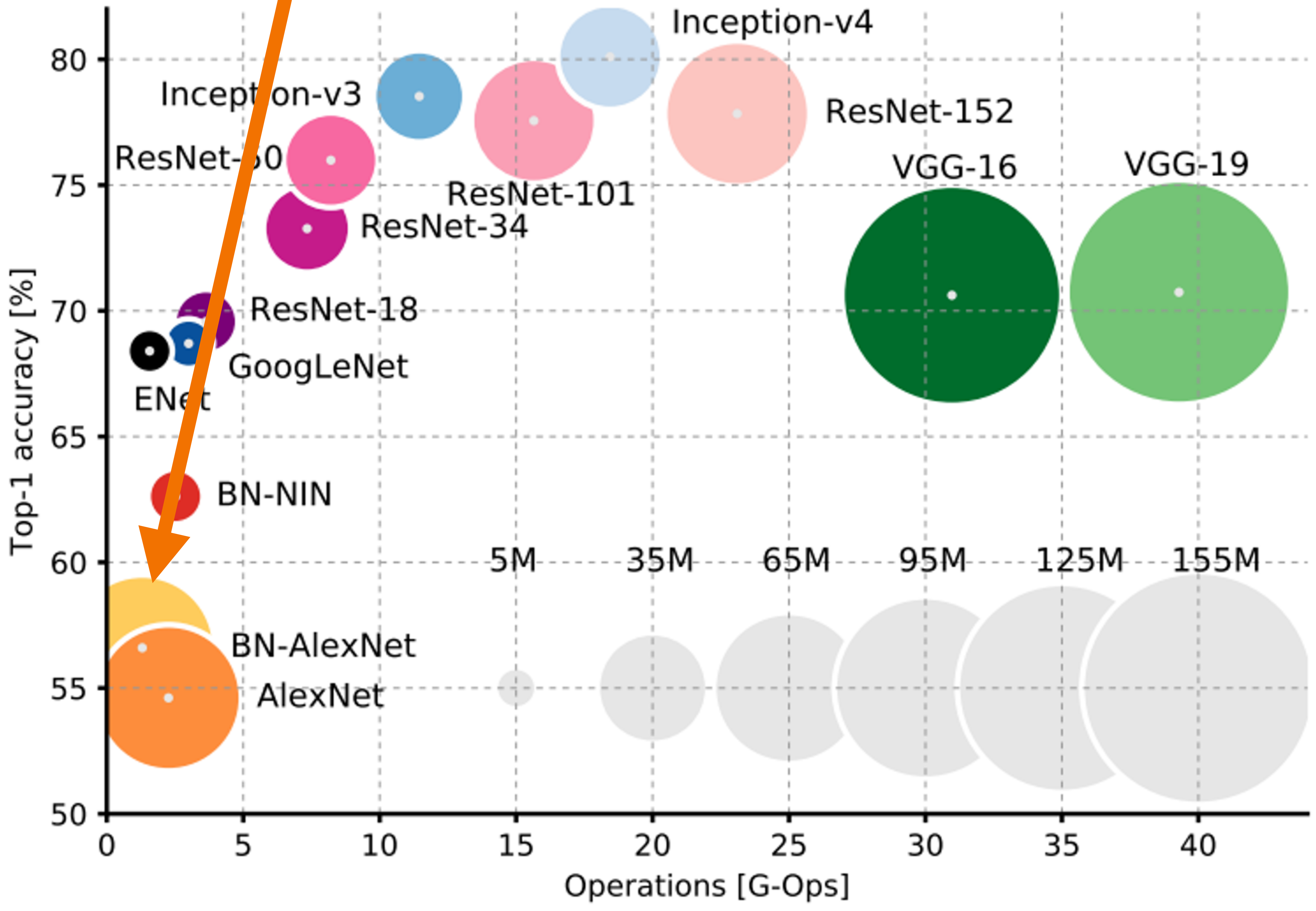


Canziani et al, "An analysis of deep neural network models for practical applications", 2017

Comparing Complexity

AlexNet: Low compute, lots of parameters

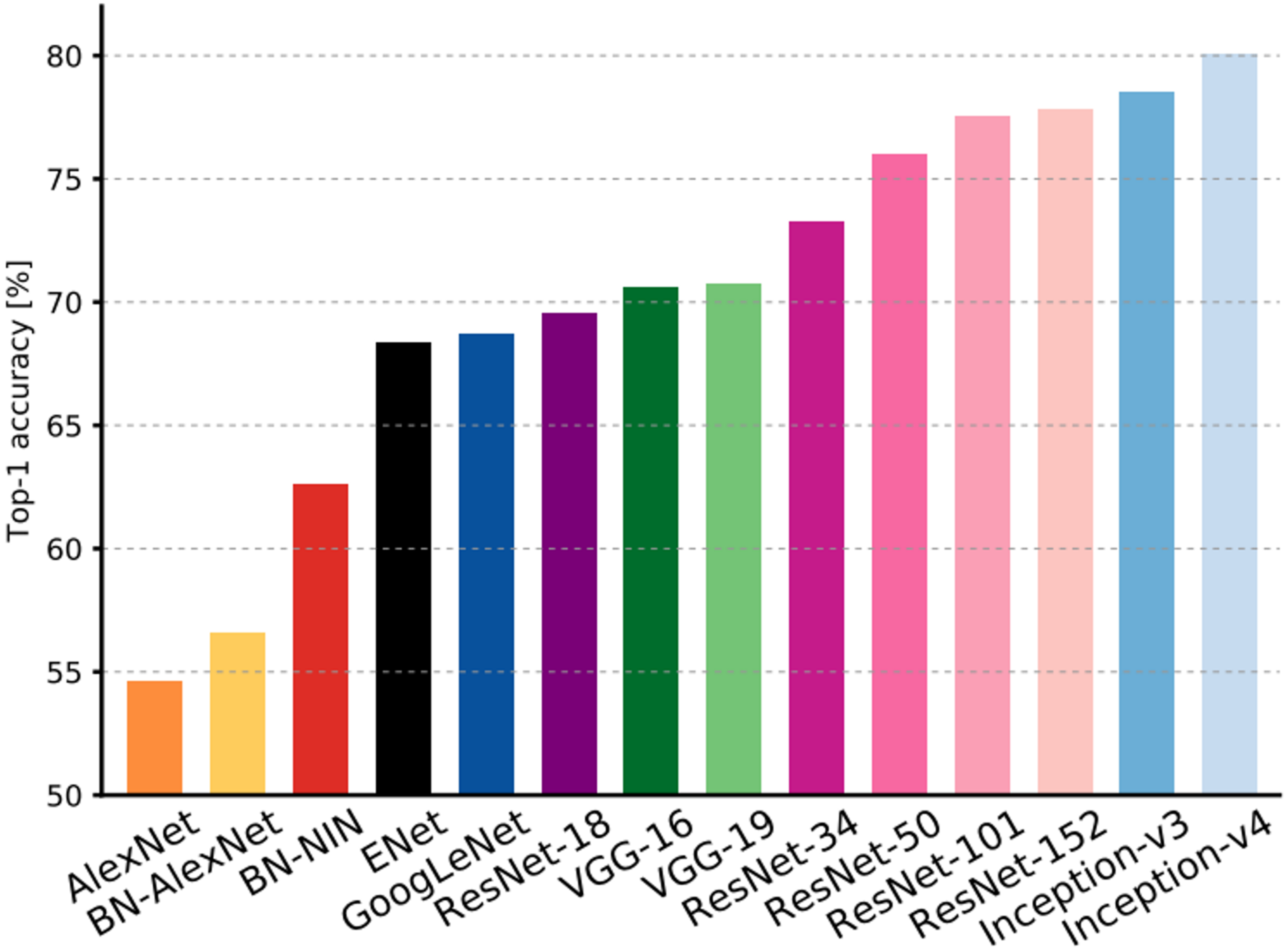


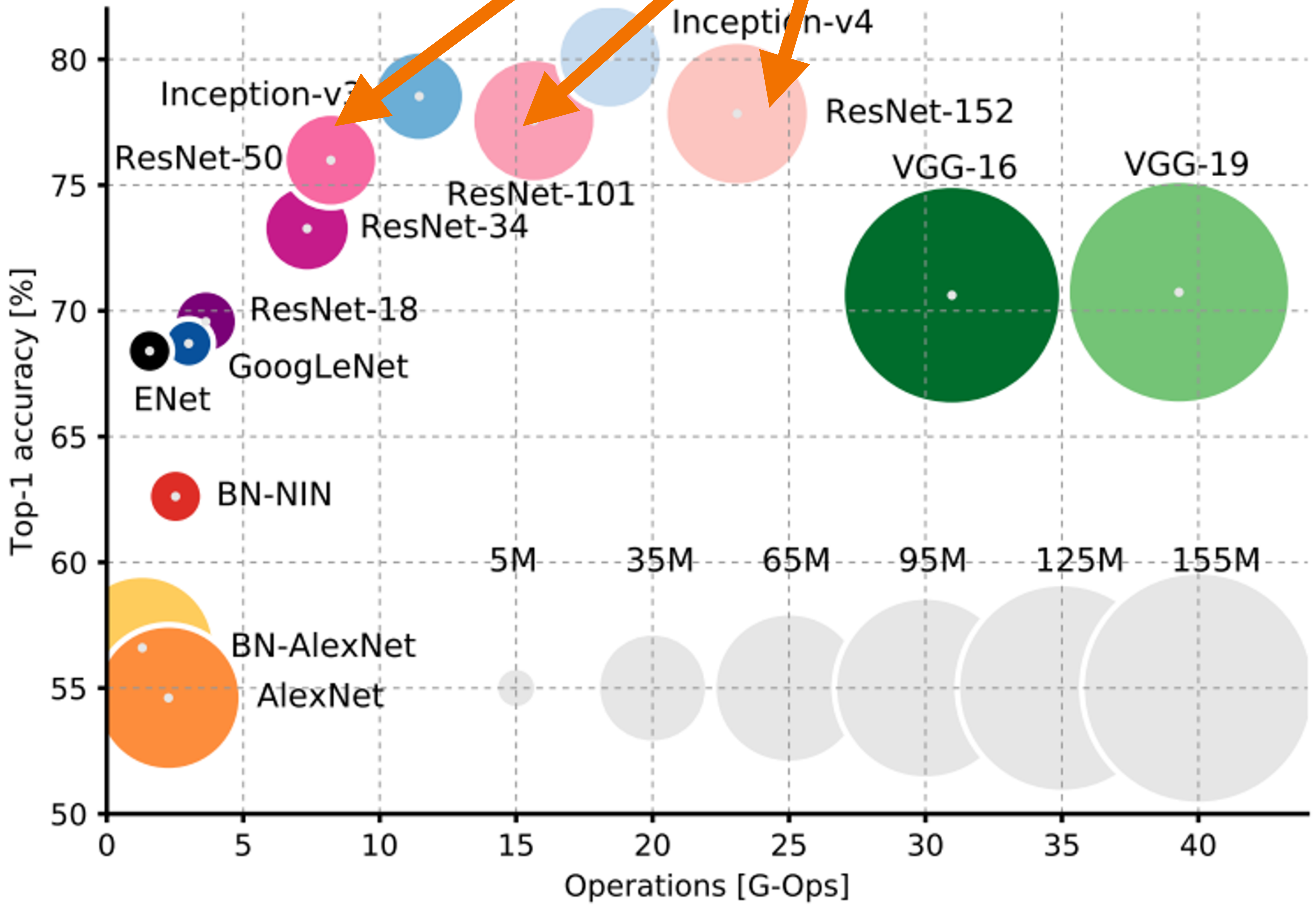


Canziani et al, "An analysis of deep neural network models for practical applications", 2017

Comparing Complexity

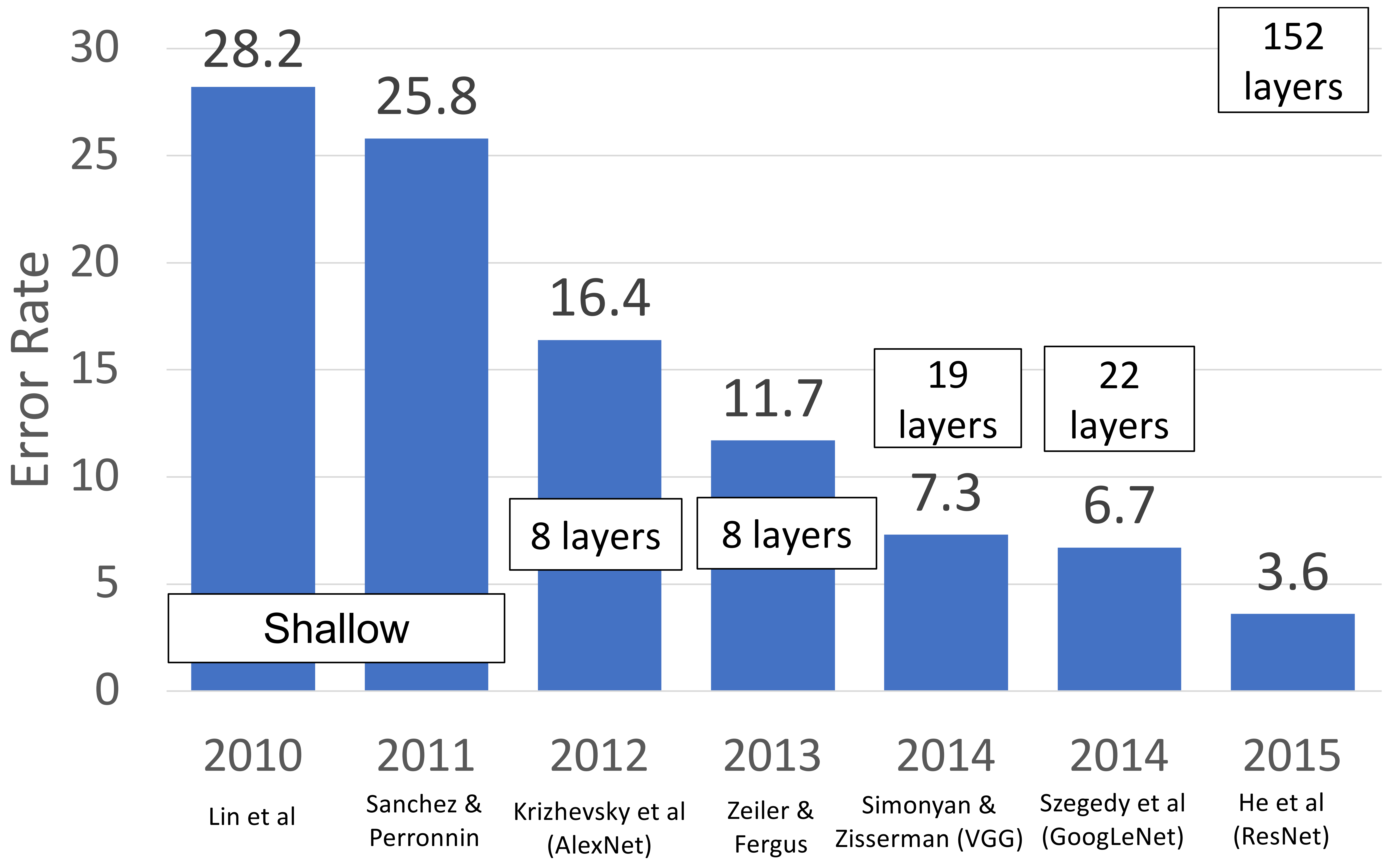
ResNet: Simple design, moderate efficiency, high accuracy





Canziani et al, "An analysis of deep neural network models for practical applications", 2017

ImageNet Classification Challenge



CNN architectures have continued to evolve!

We will see more in Lecture #

Next Time: Training Neural Networks

DeepRob

Lecture 8
CNN Architectures
University of Michigan and University of Minnesota